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DOCTORAL THESIS

In: Control

Diagnosis and Decision Aided for the Monitoring of Nuclear Reactor Systems

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بسم الله الرحمن الرحيم

ملخص

أحد التحديات الرئيسية اثناء تشغيل الأجهزة هو تحديد القياسات الخاطئة للمعطيات (الإشارات) والتحقق من صحتها.
يمكن القيام بذلك من خلال ضمان التشغيل الصحيح لمختلف الأجهزة ، وخاصة تلك التي لها أهمية كبيرة في السلامة ، ويتم ذلك من خلال اكتشاف وعزل وتحديد أي تدهور أو خطأ محتمل.
تتكون مراقبة الأعطاب ، التي تعتبر جزءًا من الإشراف على الأعطاب ، من وظيفتين أساسيتين وهما اكتشاف الأعطاب وتشخيصها. ومن جهته ، يتكون التشخيص من عدة وظائف أساسية ، منها العزل والتعرف والتحديد.
يجب إجراء هذه العملية ، المعروفة باسم مراقبة الأعطاب على الخط وفي أقرب وقت ممكن ، قبل أن يتسبب أي عطب في عطل في المعدات والذي يمكن بدوره أن يؤدي إلى تعطل شامل للمصنع وحتى إلى كوارث قاسية. وبالتالي ، فإن الإشارة المبكرة للأعطاب في هذه المعدات تصبح بالغة الأهمية ، بسبب العواقب السلبية. ولذلك فهي فعالة للغاية لأنها توفر إنذارًا مبكرًا للمشغلين وتوفرلهم معلومات ووقتًا كافيين لاتخاذ إجراءات تصحيحية وحاسمة. وبالتالي ، إذا لم يتم مراقبة أخطاء المعدات جيدًا، فإن ذلك يتسبب في تأثير خطير على التشغيل مثل زيادة وقت التعطل وإجراءات التحكم الغير السليمة ، وهي نتائج تؤثر سلبًا على الإنتاجية والتوافر والبيئة.
نظرًا لتعقيد الأنظمة الصناعية الحالية وحجمها ، مما يؤدي لمراقبة عدد متزايد من المتغيرات ما الذي يصعب عمل المشغلين.
وكحل موقت ، يتم حث المشغلين (صانعي القرار) التركيز على معالجة المعلومات الأكثر أهمية. لذلك ، يبدو مفهوم نظام الإشراف إلى جانب أداة المساعدة في القرار مهمًا للمفاعل **تريقا** (البحوث التدريبية وإنتاج النظائر الذرية العامة) **مارك اا** للبحوث النووية، مزود بمبا دلات حرارية لإزالة الحرارة المتولدة ، في الحوض المائ الذي يحتوي على قلب المفاعل ، من خلال التدفق المستمر للماء في دوائر التبريد. لذلك ، فإن مراقبة تطور الاعدادات الهيدروحرارية ضرورية لضمان سلامة المفاعل.
من بين العديد من التقنيات المتقدمة ، تم التعرف على التكرار التحليلي كطريقة فعالة لرصد الخطأ. إنها عملية تحديد أداة معيبة في النظام من خلال مقارنة ناتجها بتقدير البيانات. يستند هذا التقدير إلى النموذج والقياسات التي توفرها سلاسل الحصول على البيانات الخاصة بأجهزة الاستشعار الموجودة أثناء جميع حلات التشغيل. في عملنا هذا ، نقتصر على النماذج الرياضية **ومرشح كلمان.**
الهدف من هذه الأطروحة هو رصد واستيعاب بعض المعلمات الأساسية في القلب والمبادل الحراري لمفاعل الأبحاث النووية **تريقا مارك اا بلينا** (مختبر التطبيقات النووية) ، لأن هذه الأجهزة هي الأكثر رصد عادة. في هذه الأطروحة سنتطرق الى الشرح باسهاب الطريقة التي يستند إليها نهج الرصد ، التكرار التحليلي ، المستعمل في هذا العمل. لذلك ، فإن الدافع الرئيسي لهذا البحث هو استكشاف إمكانات الذكاء الاصطناعي ، أي الشبكات العصبية الاصطناعية ، وعلاقات الفيزياء لتصميم سلوكيات النماذج الحرة من الأخطاء وتوليد البقايا للأنظمة التي يتعين مراقبتها. في هذه الأطروحة نراجع الجانب النظري للإشراف على الخطأ أي الكشف والتشخيص والاستيعاب (بما في ذلك الطرق المختلفة المستخدمة في هذا المجال) بالإضافة إلى ذلك ، نقدم نتيجة المقارنة باستخدام طرق تحليلية مختلفة ونماذج الشبكات العصبية الاصطناعية لرصد واستيعاب بعض المعلمات للقلب والمبادل الحراري في مفاعل الأبحاث ، **تريقا مارك اا.**

Abstract

One of the major challenges in instrumentation is to identify wrong data (signal) measurements and perform their validation. This can be done by regularly ensuring a correct operation of the different process components, particularly those having great importance for safety, in order to detect, isolate and identify any possible degradation or fault.

The fault monitoring, considered as part of fault supervision, is composed mainly of two principal functions: fault detection and diagnosis (diagnostic). On the other hand, diagnosis is composed of several functions principally: isolation, identification and localization.

The operation of on line monitoring should be done as early as possible, before any fault causes failure in equipment which can lead to the downtime of the plant and even to severe catastrophes and disasters. Thus, the early indication of faults in these systems becomes highly crucial due to the negative consequences since it provides early warning to operators and gives enough information and time to take corrective or decisive actions. Consequently, if process faults are not well monitored, they cause a serious impact on process operation as the increase of the down time and the incorrect control actions. Therefore, these consequences influence negatively on productivity, availability and environment.

Due to the complexity and size of current industrial systems, the operators (decision-makers) are brought to treat (manipulate) volumes of more and more considerable information, what leads to monitor an increasing number of variable and make so difficult the work of the operators. Therefore, the conception of a system of supervision coupled with a tool of help (assistant) in the decision seems important.

At Triga-Mark II (Training Research and Isotope Production General Atomic) nuclear research reactor, the heat exchangers are provided for removing generated heat from the reactor pool water throw cooling circuits. Therefore, the monitoring of the evolution of its thermal hydraulic parameters is necessary to ensure the safety of the reactor.

Among several developed techniques, analytical redundancy has been recognized as an effective method for fault monitoring. It is the process of identifying a faulty instrument in a system through a comparison of its output to an estimate data. This estimation is based on the model and the measurements provided by the data acquisition channels of the existing sensors during all the operating modes of the installation.

The aim of this thesis is to monitor and accommodate some parameters of the core and the heat exchanger of Triga-Mark II nuclear research reactor at LENA (Laboratory of Nuclear Applications), since these systems are the most commonly monitored. We underline the theory on which the monitoring approach, analytical redundancy proposed in this thesis are based. So, the main motivation for this research is to exploit the potential of artificial intelligence and physics relationships to design faulty free model behaviors and to generate residuals for systems to be monitored.

In this thesis we review the theory of the supervision of fault (i.e., fault detection, diagnosis, and accommodation) including the different methods used in this domain. In addition, we present a comparative result by using different mathematical models, and Kalman filter and artificial neural networks approaches for the monitoring and accommodation of some parameter of the core and heat exchanger in Triga-Mark II research reactor.

Résumé

L'un des principaux défis de l'instrumentation consiste à identifier les mauvaises mesures de données (signaux) et à les valider. Cela peut se faire en assurant régulièrement un fonctionnement correct des différents composants du processus, en particulier ceux qui ont une grande importance pour la sécurité, afin de détecter, isoler et identifier toute dégradation ou tout défaut éventuel.

La surveillance, considérée partie de la supervision des défauts, est composée de deux fonctions principales : détection de défaut et diagnostic. A son tour, le diagnostic est composé principalement de plusieurs fonctions : isolation, identification et localisation.

L'opération de surveillance en ligne doit être effectuée le plus tôt possible, avant que tout défaut ne provoque une panne des équipements qui peut à son tour entraîner une panne de la centrale et même des catastrophes graves. Ainsi, l'indication précoce des pannes dans ces systèmes devient extrêmement cruciale en raison des conséquences négatives, car elle alerte rapidement les opérateurs et donne suffisamment d'informations et de temps pour prendre des mesures correctives ou décisives. Par conséquent, si les erreurs de processus ne sont pas bien surveillées, elles ont un impact grave sur le fonctionnement du processus en raison de l'augmentation du temps d'immobilisation et des actions de contrôle incorrectes. Alors, ces conséquences ont une influence négative sur la productivité, la disponibilité et l'environnement.

Vu la complexité et la taille des systèmes industriels actuels, les opérateurs sont amenés à traiter des volumes d'informations de plus en plus considérables, ce qui mène à la surveillance d'un nombre croissant de variables et rendre le travail si difficile des opérateurs. Par conséquent, la conception d'un système de supervision couplé à un outil d'aide à la décision semble importante.

Dans le réacteur de recherche nucléaire Triga-Mark II (Formation de Recherche et Production d'Isotopes Atomiques Généraux), les échangeurs de chaleur permettent de retirer la chaleur générée dans la piscine du réacteur à l'aide de la circulation d'eau dans les circuits de refroidissement. Par conséquent, la surveillance de l'évolution de ses paramètres thermo hydrauliques est nécessaire pour assurer la sécurité du réacteur.

Parmi plusieurs techniques développées, la redondance analytique a été reconnue comme une méthode efficace de surveillance des défauts. C'est le processus d'identification d'un instrument défectueux dans un système via une comparaison de sa sortie avec des données d'estimation. Cette estimation est basée sur le modèle et les mesures fournies par les chaînes d'acquisition de données des capteurs existants au cours de tous les modes de fonctionnement de l'installation.

Le but de cette thèse est de surveiller et d'adapter certains paramètres du cœur et de l'échangeur de chaleur du réacteur de recherche nucléaire Triga-Mark II au LENA (Laboratoire des Applications Nucléaires), car ces systèmes communément surveillés. Nous soulignons la théorie sur laquelle reposent l'approche de surveillance, la redondance analytique, proposée. La principale motivation de cette recherche est donc d'explorer le potentiel de l'intelligence artificielle, c'est-à-dire les réseaux de neurones artificiels, et les relations physiques pour concevoir des comportements de modèles libres défectueux et générer des résidus pour les systèmes à surveiller.

Dans cette thèse, nous passons en revue la théorie de la surveillance des pannes (c'est-à-dire la détection des défauts, le diagnostic et l'Accommodation), y compris les différentes méthodes utilisées dans ce domaine. De plus, nous présentons les résultats comparatifs en utilisant différentes méthodes basées sur les modèles mathématiques, filtre de Kalman et les réseaux de neurones artificiels pour la surveillance et l'accommodation de certains paramètres du cœur et de l'échangeur de chaleur dans le réacteur de recherche Triga-Mark II.

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General Introduction

Due to the strict requirements for the nuclear safety and the progress of technology, the dynamic of industrial process particularly *nuclear plants* (*NPs*) such as *nuclear research reactor* (*NRRs*) *(Link 1)* and *nuclear power plants* (*NPPs*) *(Link 2)* are became highly complex structural systems. This complexity is due to the introduction of new technologies which contain *control systems* substituting manual adjustments and combine at the same time large physical elements including sensors, actuators and their signal conditioning circuits; with software installed in computers. On the other hand, the *NPs* are expected to be operated with high-performance level of reliability, availability and safety for extended periods of time *(Isermann, Ballé, 1997)*. Furthermore, the preservation of the performances of the existing installations is a big challenge.

At present, the operator remains the main element in the monitoring loop. He has to analyze the situation and to take adequate decision. The reaction means to malfunctions, failures or drifts are often manual or semi-automatic. The conventional approach followed in a *nuclear reactor* (*NR*), is to monitor the value of some important parameters, such as *neutron flux*, *temperature*, *flow rate* (*FR*), *pressure*, *level*, *loose part*, *etc.*, and to generate alarms if certain thresholds values of these parameters are exceeded. However, this task is more and more difficult for the operator because of the size and the complexity of modern installations. In these conditions, the operator can make bad decisions which lead to an irreparable error. According to *(Venkatasubramanian et al., 2003a)*, 70 % of industrial accidents are due to a human error.

Moreover, the preventive maintenance strategy followed in *NR* consists in systematic tests, controls, maintenance and off-line integrity evaluation and recalibration procedures of all sensitive and critical instruments, such as *sensors (Balaban et al., 2009)*, *radiation detectors* and their associate measurement chains; and actuators and their control systems. This procedure is performed periodically (annually or monthly) during the scheduled shutdown state of the plant. However, this operation requires significant resources and takes so much time, in order to isolate the faulty instruments, then to return them back to the service. This operation sometimes is not necessary for instrumentation that is operating correctly. Otherwise, they can participate in performance degradation, aging and damaging and erroneous calibration due to repetitive manipulations. In addition, it is not an optimal method because the function conditions are only checked periodically. Therefore, faulty component can continue to operate for unknown periods up to the calibration intervals. This means, wait and the degradation continue till it causes a loss of function.

Nowadays, plants are more and more instrumented and coupled to data acquisition then, to one or several calculators and computers. Hence, the number of collected and stored data from different parts of the plant (*i.e.,* systems, processes), necessary to guarantee the normal operation of the plant, is excessive and grows constantly, and therefore even skilled human operators and experts cannot properly analyze and interpret it. *NR*s use a large number of *sensors* and *detectors* (*S/Ds*) of different types to provide continuously plant prescriptions by reading the process conditions/parameters status *(DOE Fundamentals Handbook, Nuclear Physics, Reactor Theory, 1993)*. Sensors are used to measure thermal-hydraulic parameters like temperature, pressure, *FR* of process fluid, *etc*. Detectors are used to measure neutron density, gamma and beta radiations, *etc.* These measures from many different channels are used in *safe operations*, *controls*, *radiation protection* and *monitoring systems*. Furthermore, *S/Ds* are used to measure critical plant parameters which are a required acknowledge for the safe and economical operation of *NP* systems, such as in the shutdown system envisaged by *safety and control rod acceleration movement* (*SCRAM*) *(Kasinathan et al., 2009)*. So, these components should be in healthy condition;

and their faults are one of the most common industry processes problems and their detection has been an area of an active research.

During operation of *NPs*, faulty *S/Ds* cannot provide accurate information, so it is very interesting to regularly ensure correct operation of these components, and providing the correct signal in particular for those having great importance for operating safety, in order to enhance performance and reliability *(Ray, Phoha, 2003)*. This task is known as *S/D validation (Mandal, 2015)*. Furthermore, validation of measurement of the reactor parameters using *S/Ds*; and the correct operation of associated cables and instrumentation contribute to the improvement of systems safety and hence the *plant* safety.

Many studies have shown that during operation, minor incident are more repeated, even daily. When faults and anomalies *(Anzurez-Marin, 2014; Bueno, 2007)* occur, they can seriously *degrade* the *operating efficiency* of the process which can lead to undesirable situations and have serious consequences on *economy*, *security* and *environmental*. It can force a plant into non-optimal operation and cause complete shutdown which leads to significant *production losses* and even in the worst case to *physical damage* in plant systems, human and environment *(Olivier-Maget, 2007)*. *Abnormal operating conditions* (*faults*) cost process industry billions of dollars per year. In addition, *automation* tends to *increase vulnerability* of the process to faults (*e.g.,* faults/malfunctions in process equipment, sensors and actuators, faults in the controllers or in the control loops). Therefore, failures those are associated with generation of the correct *control action* that due to invalid or faulty sensor often *lead* to *total shutdown* and catastrophic impacts.

Thus, due to the increasing *constraints*, *performance* and *quality requirements* (*e.g., availability, efficiency, reliability, safety, economy*) of modern measurement and control systems and excessive variables, parameters and stream of dynamic information; avoidance of the occurrence of unexpected failures has become a major subject that gives more attention to the monitoring of systems and process at plants.

Indeed, the human operators need new and sophisticated tools for helping to make decision during operation by continuously monitoring the performance and status of system. This insures a normal and sure operation and behavior of processes, systems and equipment; and act early in the case of occurrence of abnormal events and only the faulty component will be treated. In addition, the current generation of *NRs* has passed its mid-life, and an enhancement of plants performance monitoring is necessary to their continued safe operation.

Therefore, *continuous monitoring* is crucial of *NR* conditions by using effective methods and providing operators with exact information has been a matter of wide interest due to the increasing demands on safe and reliable operations and maintainability requirements. This allows *normal running* of the plant by *minimizing downtime*; reduction of *operation* and *intervention costs* associated with *unnecessary manual calibrations* and *maintenance*; early detection of degradation; and also providing detailed information on the performance and operation of the systems. In addition, *early FM* helps to avoid incidents; major damage to the components and machinery; process product deterioration; performance degradation; and damage to human health or even loss of lives *(Wolfram et al., 2001)*. Finally, all these benefits participate together to guarantee *the safety*, *extend the system life* of installations, and human and environmental protection. More monitoring benefits are cited in *(International Atomic Energy Agency, Vienna, 2008; Ma, Jiang, 2011)*.

Hence, it is absolutely necessary to monitor nearly all process and any drift or anomaly must be detected. Detecting a fault appearance on-line is justifi ed by the need to effectively solve the problems within a short time. After the fault has been detected, it is important to obtain information about it, which is the task of *fault diagnosis (FDi)*. *FDi* is composed of many tasks as *isolation*, *identification*, *localization*, *etc*. When the *FDi* is limited to *isolation* or to the *identification* of fault, in this case the *monitoring* is called *fault detection and isolation* or *identification* (*FDI*). The succession of *fault detection (FDe),* and *FDi* constitute the *FM* structure. Therefore, the task of a monitoring system is to use the different measurement data from *S/Ds* to establish information regarding the fault condition of the *NP* (*Figure* 1).

Once a sensor failure is detected and diagnosed in the *monitoring* stage, the *accommodation* replaces the faulty component (*i.e., S/D*) reading with a reliable estimate. In this work, the faulty *S/D* reading substitution is made by using *NN*s and *analytical models (Hussain et al., 2013;Samy et al., 2011)*. So, the association of *FM* and *accommodation* can be seen as a *supervision of fault (Olivier-Maget, 2007)*.

Indeed, in the last few decades, *on-line condition monitoring* and *accommodation* has become a significant issue to ensure stable operation and to achieve higher plant operability. Especially, it is more important for old *reactors* to detect the symptom of anomalies and to deal with them at the beginning of serious accidents.

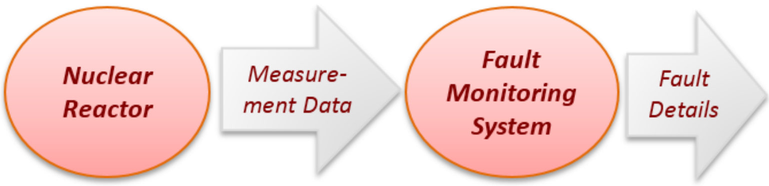


Figure 1 - Monitoring system.

To set up a monitoring system, it is necessary to have detailed knowledge on the installation in both normal and abnormal situations. This knowledge includes basically the nature of fault causes; the associate symptoms to the faults induced by their causes and the different processing tools of these symptoms; and physics of the mechanisms between causes and effects. More details on this knowledge is available in *(Olivier-Maget, 2007)*. Nevertheless, in the reality, it is sometimes difficult to have this exhaustive knowledge and only a subset of these elements is usually available.

The development of an on-line *FM* procedure must be able to answer to some constraints *(Orantes Molina, 2005)* such as the temporal characteristics of fault are unknown; system model (if it is available) is vague; noises of the model and measures are taken into account; and operation in real time by minimization of *FDe* and *FDi* time *(Olivier-Maget, 2007)*.

According to the literature, important applications on the monitoring of processes and equipment in *NPs* have been performed with success in many different fields, such as *reactor internal parts vibration monitoring*, *loose part monitoring*, *instrumentation monitoring* (*e.g., sensors*, *actuators*), *reactor core parameters monitoring*, *transient identification*, *equipment condition monitoring* (*e.g., rotating machinery*), *waste water treatment process (Ma, Jiang, 2011)*, *etc*.

Beside *nuclear* field, a wide range variety of approaches have been studied and developed for the *fault monitoring* (*FM*) in industry such as *aeronautical systems* (*e.g.,* aircraft control system, navigation system and engines); *chemical plants* and *petrochemical processes*; *gas turbines* and *power generation*; *embedded control systems in vehicles*; *industrial robots* and *electric motors*. These *FM* methods have been reviewed in a number of books and papers *(Ding, 2012; Ma, Jiang, 2011; Onchis et al., 2014; Yan et al., 2014; Zaytoon, Lafortune, 2013)*.

FM methods distinguish themselves according to various criteria: the dynamics of the process (*discrete*, *continuous*, *hybrid*, *linear* or *non-linear* (*NL*), the implementation of the monitoring system (*on/off-line*), the nature of the information (*qualitative* and/or *quantitative*), and the type of use (*centralized* or *distributed*). Each of these competing methodologies has their own distinct advantages and disadvantages, as reviewed by *(Olivier-Maget, 2007)*. Therefore, many classifications of *fault detection and diagnosis(FDD)* technics are suggested. The renowned and the most used among these classifications, the one which groups the methods in *two categories*: *analytical model* and *free model- based methods (Khireddine, 2014)*. However, others reach till five groups of classification such as that given by *(Ma, 2015)*: *signal-based methods (SiBMs)*, *data driven methods (DDMs)*, *model-based methods (MBMs)*, *pattern recognition* (*PR*) *methods*, and *data fusion methods*. In *NRs* many systems and equipment require a continuously monitoring because their parameters are critical so, the validation of these parameters is become more than a necessity.

The aim of this thesis is to monitor and accommodate some parameters of the *core* and the *heat exchanger* (*HE*) of *Triga-Mark* II (*Training Research* and *Isotope Production General Atomic*) *NRR* at *LENA* (*Laboratorio Energia Nucleare Applicata*), since these systems are critical and the most commonly used. To get a satisfactory performance and a safe control operation, the application of redundancy based on mathematical modeling and *NN*s is used because it presents a powerful challenge. The developed system will assist the operator to treat and identify, as early as possible, such initiating events quickly and to take corrective actions so that the system can operate in an acceptable manner to prevent system shutdown.

This thesis is organized into *five chapters,* starting by *general introduction* and ending by general *conclusions. General introduction* in describes the encountered problematic at industrial plants, particularly in *NRs*, with the technology advancement in point of view safety and efficiency. Then, we propose the online supervision as the best solution to help the operators to encounter the actual challenges. In *Chapter I,* we give a general description of *Triga-Mark II reactor* at *LENA* particularly, the *core* and *hydraulic circuits* including *HE,* systems concerning by the monitoring in this work. For the core, a presentation of the configuration (fuel elements, control roads) is given. For the *HE*, the description includes details on architecture and characteristics. Furthermore, an overview on the scheme of the data acquisition set of these two previous systems is provided. Since some nuclear parameters of the core are concerned by the monitoring in this work, we considered necessary to introduce some physics-based approaches used for their computation. In addition, this chapter deals with the *mathematical- based modelization techniques* and *Kalman Filter (KF)*, used to predict temperatures and *FRs* of the *HE*. *Chapter II* deals with a general concept of *supervision*, including the *monitoring* and *fault control*. In this context, we illustrate the different manner the faults are manifested and methods to be used to treat them. *Chapter III* presents the main approaches used in the *FM* domain. So, the sample group of monitoring methods is considerable *(Isermann, Ballé, 1997; Persin et al., 2002)*. The purpose of *Chapter IV* is to present the *NN* applications in the *FS* of systems. So, this chapter deals with *NN*s, considered as part of *artificial intelligence (AI)* and *DDM. NNs are* more interesting when a model of equipment does not exist or is difficult to obtain. For efficiency applicability, we introduce an overview on the *NNs* concept dedicated to *FDe* particularly, architectures proprieties and applications. The *SNN*s can offer very interesting solutions in stationary applications but cannot be applied to data where time plays a determining role in the resolution of the problem. So, the representation of time in *NNs* represents an essential characteristic in the perspective of a dynamic system monitoring. *Chapter V* presents the application of the analytical techniques and *NNs* for the prediction of parameters of the core and the *HE* of the reactor. Then, this prediction is used in the location and accommodation of faults. Results of estimation by using the two main methods and schemes for *FDD* and accommodation are presented and discussed. We end up by a *general conclusion* and *perspectives*.

CHAPTER I

Description of the Reactor, Core Parameter Physics and Thermohydraulic of Heat Exchanger

In this chapter, we give a general description of the Triga-Mark II reactor at LENA; its core and hydraulic circuits, systems concerning by the monitoring in this thesis. Since our objective is to supervise some parameters of the core and the heat exchanger, we began by an overview of these equipment and process structure then, we make a recall on some approaches of physics used for the computation of these parameters.

I.1 - Description of the Research Reactor

I.1.1 - Introduction

TRIGA (Böck, Villa, 2007; Coban, 2014) reactors stay as the most widely used *research NRR* in the world. It is a small nuclear research and education reactor constructed for use by universities, scientific institutions, industrial laboratories, and medical centers for peaceful purposes such as *training*, *research*, *testing*, and *radioisotope production* for medicine and industry, treatment of tumors, nondestructive testing, basic research on the properties of matter, and for education and training (Mesquita et al., 2009). It is not intended for energy generation. The most important feature of the *TRIGA* reactor is its fuel element which is a combination of slightly enriched uranium as fuel and zirconium hydride as moderator. It provides the reactor a prompt negative temperature coefficient and thus a high level of security. The *Mark-II reactor* (Nacir, 2013; Smodiš, Snoj, 2010) is a variant of the *TRIGA NRRs.*

The *Triga-Mark II* at *LENA* of *University of Pavia* is an open pool type using light water for the cooling and moderation functions, and annular graphite reflector. It is in operation since 1965 at a maximum steady-state power level of 250 kW (General Atomic, Division of General Dynamics, 1964). Reactor core configuration is given on *Figure I.3.* The reactor operates with solid fuel elements which are cylindrical rods with stainless steel cladding. It contains a homogeneous mixture of zirconium hydride (ZrH) moderator combined with uniform mixture of uranium (8% *wt* enriched at 20% in 235-U) (Coban, 2014). This particular composition has a large, prompt negative thermal coefficient of reactivity (ρ). This *NRR* has been used for several scientific and technical applications such as production of radioisotopes, nuclear activation analysis and development of boron neutron capture therapy in the medical field and reactor physics studies.

I.1.2 - Cooling Circuits

Fission of the nuclear fuel inside the core produces the warming up of the primary circuit water. Fluid is circulated by the primary pumps. The heat produced is transmitted to the secondary circuit and then the tertiary circuit through two *HEs* respectively. The cooling of the reactor core is made by natural convection which transfers the heat of fuel gain to the water inside the tank. When the reactor works at the nominal power of 250 kW, without heat extraction system, the temperature of water increases with a rate of 13.3$°C/h$. The fuel elements in the reactor core are cooled by natural water circulation. An active heat removal system draws water from the reactor pool and released into the atmosphere. This is done through two *HEs* from the *primary* to *secondary* and then *tertiary* cooling loops (*Figure I.1*).

The primary cooling circuit is composed of a water pump and a thermal *HE* which extracts the heat from the water tank and then transfers it to the secondary cooling circuit. The primary pump starts automatically when the temperature of water becomes higher than 30 $°C$. The output of the primary circuit is situated at the top of the reactor core, so when the primary pump works, a flow of cold water decreases the level of temperature in the core and consequently the ρ increases. In this circumstance, an automatic controller of power of the reactor is applied to maintain a constant level of the reactor power.

Both installed *HEs* are *shell-and-tube* type as show on *Figures I.1* and *I.2.* Their characteristics are given in *Table I.1*. In the cooling loops of *Triga-Mark II reactor*, we find different types of sensors such as *platinum resistance thermometers, flow meter* and *pressure transmitters*. For *radiation detectors*, we find *ion chamber* used to control the *Pn* level by measuring neutron flux. The *inlet* and *outlet temperatures* are measured by *platinum resistance thermometers* (*PT*-100) positioned at the inlet and at outlet pipes of the *primary*, *secondary* and *tertiary* cooling loops.

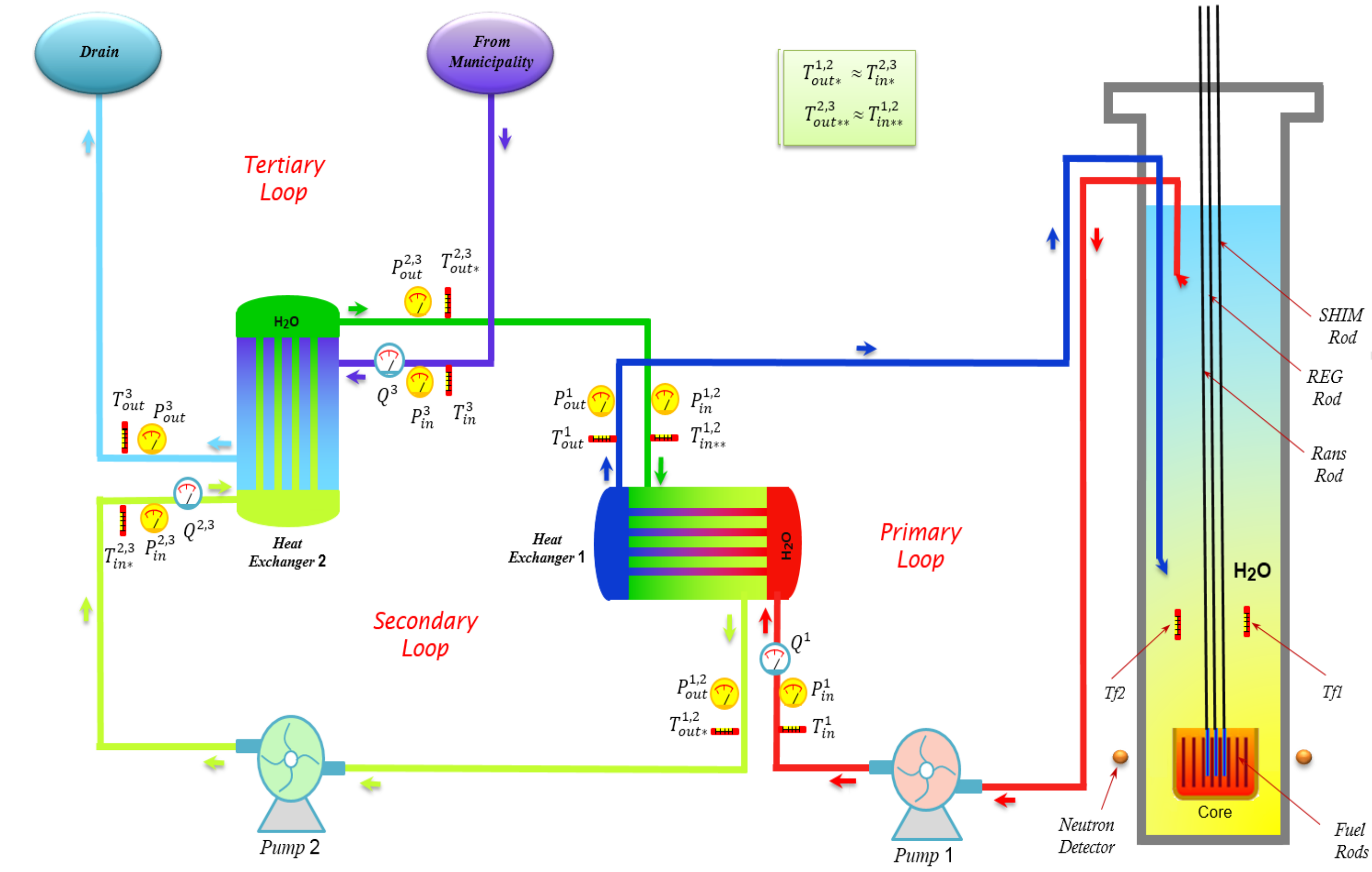


Figure I.1 - Schematic presentation of the cooling circuit of the reactor core, where Q, T and P indicate the FR, the temperature and the pressure, respectively.

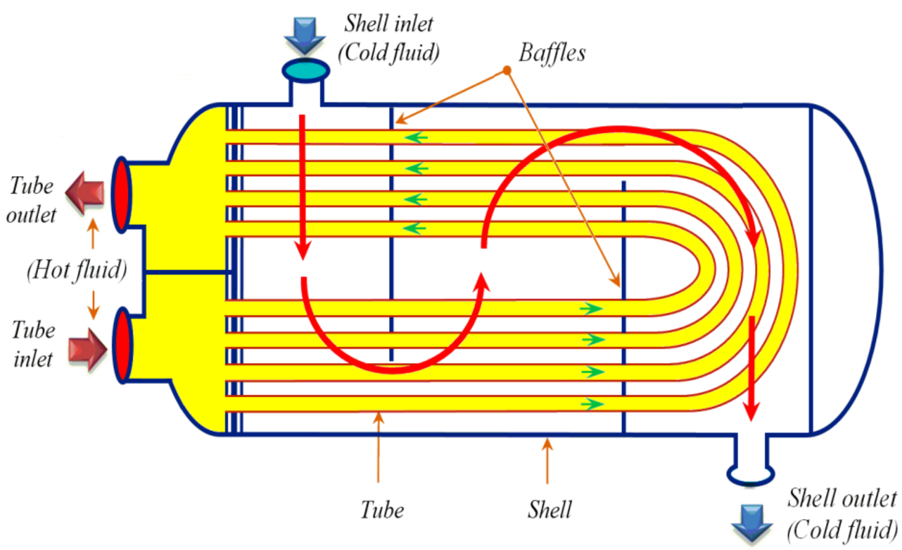


Figure I.2 - Both HEs are shell-and-tube.

The *FR* in the *primary* cooling loop is measured by *ultrasonic flow-meter* and in the secondary and tertiary cooling loops is measured by *electromagnetic flow meters*. The pressures in the inlet and outlet of the three cooling loops are measured by *pressure transmitters*. The *Mass Flow Rate* (*MFR*) in the *primary*, *secondary* and *tertiary* cooling loops are in the range of 9.2, 8.9 and 6.7 kg/s, respectively, as recorded during the experimental campaign (*March* - *May* 2016).

Designation	HE 1	HE 2
Number of tubes.	72	45
Length [m].	4.20	4.50
Outer diameter [cm].	40.6	50.6
Weight [kg].	997	1100
Exchange capacity [kW].	255.81	439.53.
Tube Bundle.	Stainless steel AISI 304, outside diameter of 18 [mm] and inside of 16, 6 [mm].	
Shell.	Stainless steel AISI 304.	

Table I.1 - Technical characteristics of HEs of Triga II reactor at LENA (General Atomic, Division of General Dynamics, 1964).

I.1.3 - Core

The reactor core is placed at the bottom of a cylindrical aluminum tank with a diameter of 1.98 *m* and a high of 6.25 *m* and filled with natural water. So, the total quantity of water which the pool can contain is about 18 m^3. An annular graphite reflector (with an inner diameter of 45.7 *cm*) enclosed in the tank surrounds the core. The water and the concrete establish a protection against radiations for the staff working near the reactor. Two grid plates allow the placement of the 91 core elements in six concentric rings as shown on *Figure I.3.* Each location corresponds to a hole in the aluminum upper and bottom grid plates of the reactor.
Two fuel elements, equipped with thermocouples as given by *Figure I.4,* are used to measure temperature inside fuel material. They are located one at the center of the fuel horizontal line and the other two 2.54 *cm* above and 2.54 *cm* below the center.

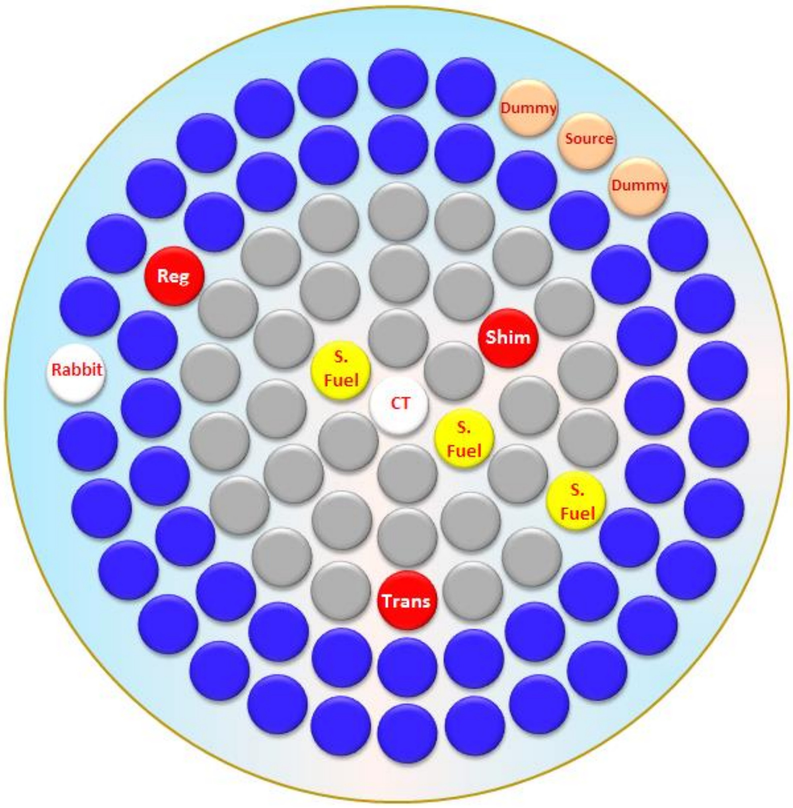


Figure I.3 - Reactor core configuration. At the center, top view of the core configuration and the regulation, shim and safety control rod positions corresponding to the position filled in red. The positions filled in blue correspond to fuel elements with aluminum cladding. The positions filled in grey correspond to fuel elements with stainless steel cladding.

The *TRIGA* control system of the ρ consists of *three* neutron-absorbing control rods: *regulation, transient* and *shim* or *safety rods (Mesquita, Souza, 2010; Coban, 2014).* The position of the three control rods within core configuration is given on *Figure I.3.* The role of control rod is to achieve ρ control and reactor scram. It is one of the important guarantees for reactor safety. The *transient* rod, formally used to pulse the reactor, is used for the safety and during normal operation of the reactor; it is kept outside of the core. The *shim* rod is designated for the coarse changes of ρ as the *fuel temperature* (*Tf*) feedback and the poisoning. The *regulation rod* serves to adjust the reactor power to the desired value handling small variations may occur. It is positioned in the outer region of the core; as a consequence, its ρ worth is less than *shim* and *transient* worth.

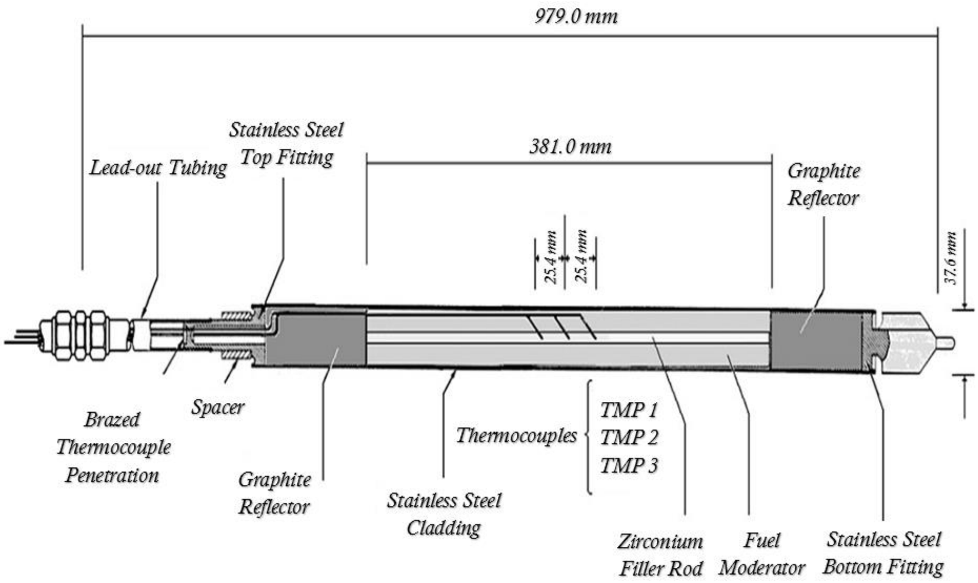


Figure I.4 - Representation of the combustible element.

The control rod drive mechanism is represented on *Figure I.5.* It consists of a two-phase electric motor that actuates a linear drive equipped with a magnetic coupler (*i.e., the magnet draws tube*). Its purpose is to adjust the control rod position in order to control reactor power. Unlike the transient rod, which is pneumatically operated, the regulation and shim control rods are moved through this system. Regulation and shim rod motion is controlled from the console by energizing the magnet and motor, which rotates the pinion gear shaft on rack causing the vertical displacement of *magnet draw tube* and so of the control rod. If the electromagnet is energized, the armature and the connecting rod will rise with the draw tube so that the control rod is withdrawn from the reactor core. In the event of a reactor scram, the magnet is de-energized and the armature will be released, the control rods will then drop for gravity into the reactor core. During a reactor scram, all the three control rods are completely insert in reactor core within 400 *ms*. The *shim* and *regulation rods* move with a constant speed of 29 cm/min, however a direct measure of regulation rod with draw velocity has provided 21.92 cm/min.

The knowledge of the reactor's response to the controls rod motions is necessary to the safe and efficient operation of a *NR*. The effectiveness, or worth, of a control rod depends largely upon the value of the neutron flux at the location of the rod. Each rod position is read through a potentiometer and it is displayed on the console in digit unit. When the *shim* or *regulation* rod is completely extracted, its value is 825 *digits* and when the rod is completely inserted; its value is 125 *digits*. Therefore, the rod excursion, in digit, is Δd = 700. The total vertical displacement of control rods, Δh, is about 38 *cm*, 19 *cm* above the *core* mid line and 19 *cm* under the *core* mid-line. Therefore,

$$\frac{\Delta_d}{\Delta_h} \approx 18\ digits/cm \tag{I.1}$$

The position of the control rods is measured with respect to the fully insert position which correspond to cover the entire active fuel length, as represented on *Figure I.6.*

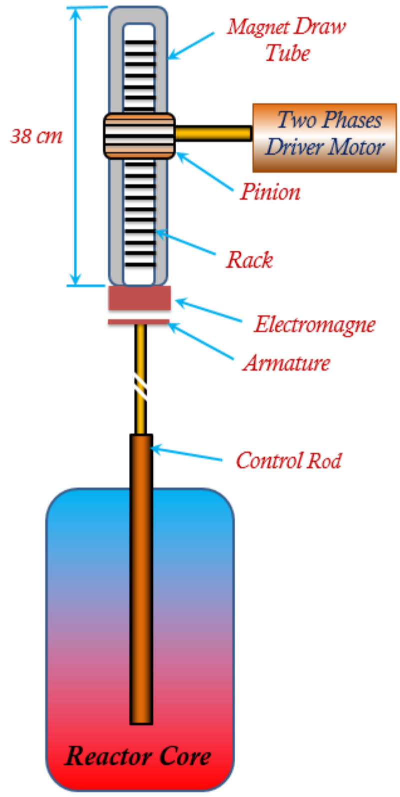


Figure I.5 - Rack and pinion command for the control rod "Regulation" and "Shim".

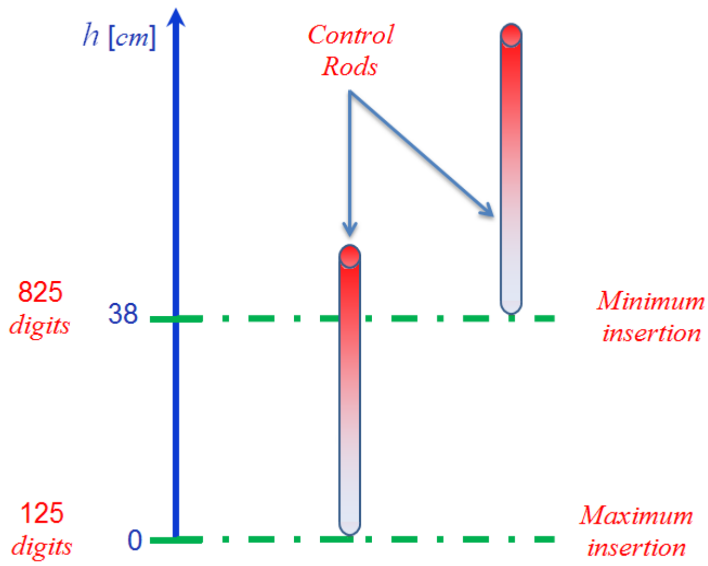


Figure I.6 - Position of the control rod in comparison with the active length of the core.

I.1.4 - Data acquisition system

The *Data Acquisition System (DAS)* of the *LENA NR* is given by *Figure I.7.* It consolidates information about the reactor status by collecting the measurement of various operational parameters from different systems, as *time series data*, periodically in each one second, from a network of instruments/sensors distributed on the plant. The *DAS* control several operational parameters, including temperature, *FR*, level, pressure, nuclear radiation, *Pn*, safety and control rod position then it provides an on-line data analysis and transfer these parameters to the supervisor *PC* for display and management *(Mesquita, Rezende, 2010)*. *DAS* allows also storing the temporal history of all the process variables, thus supplying the data that will be used in the monitoring of the system. The data acquisition module should include signal isolation and conditioning devices as well as fast sampling capabilities.

The *DAS* is made of *PLC*-type (*NI Compact Field Point TM*) and dedicated analog input cards for data sampling. The standard for data transmission is 4-20 *mA* current loops and, depending on the device, the loop is powered either from an external power supply or by the device itself.

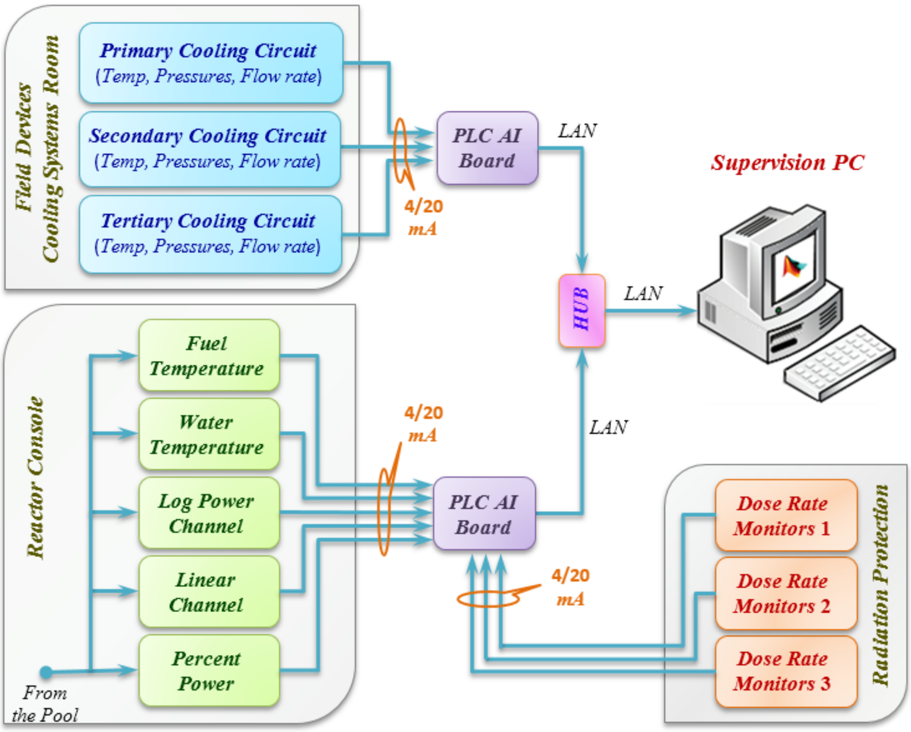


Figure I.7 - Data acquisition of the NRR *of* LENA.

The reading of the power of a *NR* is, usually, made continuously by the direct measurement of the average *core flux* using neutron detectors. The reactor power varies from *mW* to *kW* therefore, it is necessary using a decade instrumentation to monitor the entire operating range (from source strength to full power output). For this purpose, at *LENA* reactor, the power is monitored by *four* independent *neutron-sensitive detectors* mounted outside the *reflector* surrounding the reactor *core* as given by *Figure I.8*. These *three* detectors *ion chambers*, two *compensated* and one *uncompensated*, and a *fission chamber*. Each detector is enclosed in a seal aluminum container. The four detectors are located around to the core reflector using the ring. They are all calibrated by the thermal method, considered as standard procedure for power of the *TRIGA II*

The signals coming from the neutron detectors are carried to reactor console form *three* independent measurement channels to cover the entire operating range (from source level ~ *mW* to full power output ~ *kW*) as shown on *Figure I.9*. *First*, the *linear channel* consists of a *compensated ion chamber*, whose output signal is connected to a *sensitive amplifier* which gives accurate power reading, from source level to full power on a *linear recorder*. *Second*, the *logarithmic channel* consists of the *fission chamber* whose output signal is connected to a *logarithmic amplifier* which gives a *logarithmic power* reading from less than 0.1 *W* to full power 250 *kW* on recorder. *Third*, the *percent channel* consists of *uncompensated ion chamber,* whose signal is calibrated in percentage of full power which provides a *perceptual analogic indication* at the reactor console.

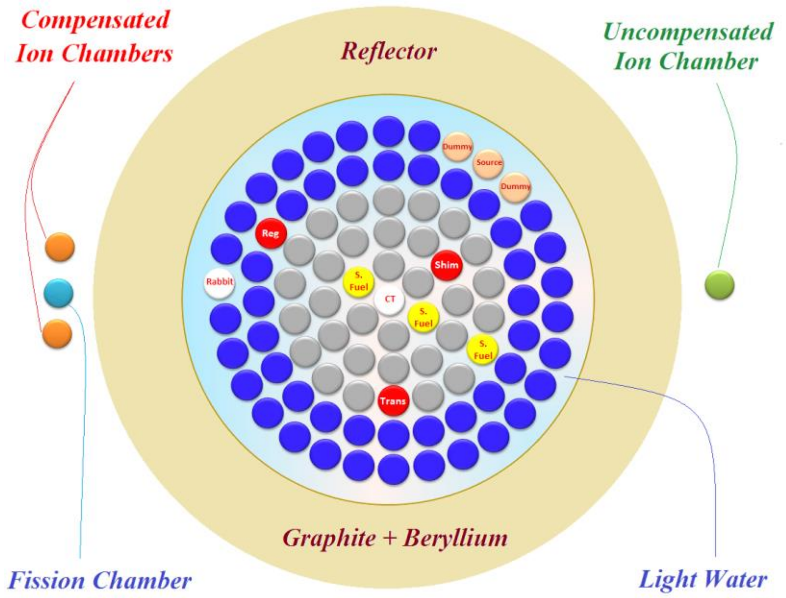


Figure I.8 - Power is monitored by three independent neutron-sensitive detectors mounted outside the reflector surrounding the reactor core.

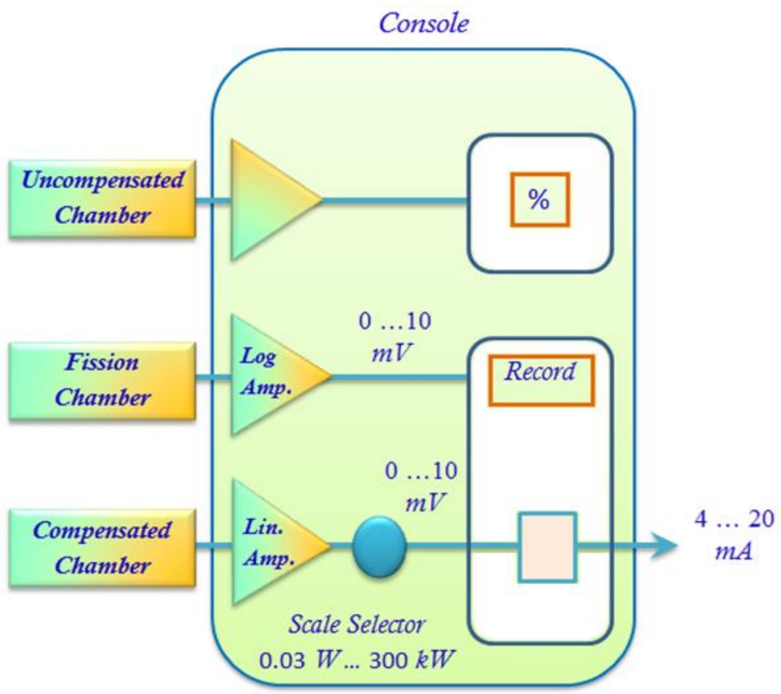


Figure I.9 - Presentation of the measurement channels.

The *departure channel* consists of a *fission counter* with a pulse amplifier that a *logarithmic count* rate circuit and gives useful power indication from the neutron source level up to a few watts. The *logarithmic channel* consists of a *compensated ion chamber*, whose signal is the input to a logarithmic (*log n*) amplifier, which gives a *logarithmic power* indication from less than 0.1 *W* to full power. The *linear channel* consists of a *compensated ion chamber*, whose signal is the input to a sensitive amplifier and recorder with a range switch, which gives accurate *power information* from source level to full power on a linear recorder. The *percent channel* consists of *an uncompensated ion chamber*, whose signal is the input to a *power level monitor circuit* and *meter*, which is calibrated in percentage of full power. The last three channels were adjusted with the results of the *thermal calibration* described here *(Mesquita et al., 2007; Mesquita, Rezende, 2010).*

I.2 - Core Parameter Physics

In the reactor core, there are several parameters to control: hydraulic (*e.g.*, *temperatures*, *pressures*, *FRs*), nuclear (*e.g.*, *Pn*, ρ) and other parameters limitations are usually, on-line supervised to ensure that the core is operated within the thresholds and assumptions made in the safety analyses. For example, in-core temperature measurement is a critical issue for the safe operation of *NR*s. Classical thermocouples require shielded connections and are known to drift under high neutron fluency.

I.2.1 - Nuclear Power

Control of a *NR* power level is challenging since the dynamic of the reactor is very complex, *NL*, time-varying, also includes saturation, dead time, and changes with operating conditions. A major current effort to improve the availability of *NPP* is to assure that the plant operator has *accurate* information about the *power level*.

I.2.1.1 - Measurements

The *reactor power measurement* technics can be roughly divided into *two* main *categories*. The *first* is done *directly*, based on nuclear physics measurement method which measures the fission rate of the fuel elements in the reactor by means of the *period (Amblard, 1968),* the ρ, or by measure of the *neutron flux* through one or more appropriate *neutron detector*. So, the output signal of detector (voltage for proportional counter and current for *fission chamber*) is directly proportional to the *thermal neutron flux*, ϕ. The *second* is done *indirectly* usually, by *thermal procedures* (*i.e.,* it measures the heat generated by the *reactor*), like *calorimetric* and *balance of energy* methods. The *first category* of *methods* can be used in *OLM* but the *second category* can only be used for *calibration* of power in *NRs*.

For the control of a *NR*, the evolution of the power is deducted from the measure of the reactor period (time of doubling). This period which is defined as being the opposite of the logarithmic by-product of the neutronic stream, does not always establish (constitute) a precise reflection of this evolution *(DOE Fundamentals Handbook, 1993)* :

$$P(t) = P_0 \exp(t/T_p) \tag{I.2}$$

where P_0 is the *initial reactor power*, *Tp* is the *reactor period* (in *seconds*), *t* is the *time* during the reactor transient (in *seconds*). *Tp*, usually expressed in units of *seconds* or *minutes*, is defined as the time required for the neutron flux to change by a factor e = 2.718. However, this period which defined as being the opposite of the logarithmic by-product of the stream neutronic, does not always constitute an accurate reflection of this evolution *(Amblard, 1968).*

In the ideal case the output signal $n(x)$ of the detector at a place x is directly proportional to the *NR power* *(Merljak, 2013)* :

$$P(x) = K_x T(t, x) \tag{I.3}$$

Where K_x being a predetermined coefficient; $K_x \approx 7.03 \pm 0.16\ kW/\mu A$ *(Trkov, Ravnik, 1995).*
Multiplying the reaction rate by the volume of the reactor results in the total fission rate for the entire reactor. Dividing by the number of fissions per *watt-sec* results in the power released by fission in the reactor in units of *watts*. So, the *power output* of a *NR* is directly *proportional* to the *neutron flux* in the *core* given by:

$$Pn = \frac{\Phi \Sigma_f V}{3.12\times10^{10}\ (Fission/Watts{-}Second)} \tag{I.4}$$

where Pn is the *power* (*Watts*), Φ is the thermal neutron *flux* (*neutrons/cm-sec*), Σ_f is the *macroscopic cross section* for fission (*cm*-1) and V is the *volume* of the *core* (cm^3).
From *Equation I.4*, Pn and Φ are directly *proportional,* since: (*a*) V is *constant* for a given reactor; (*b*) Φ is also relatively *constant* over a relatively short period of time (some days or weeks; (*c*) Σ_f must also be *constant* as the *atom density* and *microscopic cross section* are constant. But indeed, over a period of months, Φ, for a given power level will *increase* very slowly due to the burn-up of the fuel, and consequently *atom density* and Σ_f *decrease*.

Neutron flux measurement is made with specific *neutron detectors* with two manners: usually, with *BF*3 *counter* or an *ionization chamber* outside of the reactor *core* (*Figure I.8*) where the neutron flux is lower or by a *miniaturized fission chamber*, located in the reactor *core* which can be operated at any temperature up to 300°*C* *(Merljak, 2013).* Since these *neutron detectors* measure only the local flux at their position, thus the measurements are not always proportional to the total neutron flux (*i.e.,* integral neutron flux) in the *core* and consequently to the *core* power. Therefore, the total neutron flux in the reactor must be estimated indirectly from neutron detector measurements through the *calibration procedures* cited bellow.
The neutron detector gives a signal output n_x, assumed directly proportional to the thermal neutron flux, Φ_x, at the position x.

$$n_x = K_x \Phi_x \tag{I.5}$$

where K_x being a predetermined coefficient.
However, owing to stability conditions of parameters of *Equation I.4* (*i.e., core* configuration is constant) discussed previously, the *Nuclear Power Reactor (NPR)* is assumed proportional to Φ_x, and therefore to the *neutron detector signal*, n_x.
For a small *core NR*, the absolute power is permanently obtained from the calibrated neutrons detector because no changes in *core* configuration or in control element arrangement is undertaken during long periods of operation. With the reactors in which the outputs exceeding 100 *kW*, it is required to calibrate the neutrons detector frequently for correction of sensitivity to conform to occasional changes of *core* arrangement.

The *thermal neutron flux* achieves its *maximum value* in the *center of reactor* but is *reduced* at *extreme ends* of the *reactor core*, since very few thermal neutrons are produced in this area. Hence the *flux distribution* is *strongest* at the *middle of the reactor's core (Ahmed et al., 2008).* However, the *average flux* of a reactor is a *variable parameter* that *depends* on the *reactor's moderator* and *coolant temperature.*
Cherenkov radiation is also used to measure power in *NRRs* with a good sensitivity in parallel with the existing conventional *detectors*. However, this *monitoring* method is independent of *core* configuration and *burn-up* and is applicable over large range which makes it useful for calibration of control instruments. However, its linearity in the low power range is worse *(Arkani, Gharib, 2009; Rippon, 1963).*

I.2.1.2 - Calibration

The *knowledge* of the *reactor thermal power* is very important for precise neutron flux and fuel element burnup calculations. The burnup is linearly dependent on the reactor thermal power and its accuracy is important to the determination of the mass of burned U^{235}, fission products, fuel element activity, decay heat power generation and radio-toxicity *(Mesquita, Rezende, 2010).*

Power monitoring of *NRs* is always done by means of neutronic instruments, but its calibration is done by thermal procedures. For the *thermal power calibration* of a *NR*, there are two procedures: the *calorimetric* *methods* and the *heat balance* *(Zagar et al., 1999; Mesquita, Rezende, 2010).* Their common methodology consisted of the measurement of the power dissipated at the primary loop and the calculation of the heat losses. The *calorimetric method is* the standard procedure for calibrating the power of the *TRIGA II reactor (Mesquita et al., 2007).* The *thermal balance* method is a standard methodology used for the *TRIGA* Reactor power calibration *(Mesquita, Rezende, 2010).* The intensity of the distributed gamma rays from the reactor *core* is proportional to the reactor power; therefore, gamma rays counting is used as *on-line calibrated method* for reactor power measurement. This technique is less sensitive to perturbations and independent of control rods and fuel configuration of the reactor *(Czaika, Kerr, 1969; Jalali et al., 2013).* However, the calibration by using *calorimetric method* presents a large uncertainty. The main source of error was the determination of the heat content of the system, due to a large uncertainty in the volume of the water in the system and a lack of homogenization of the water temperature *(Mesquita et al., 2009).*

Other methods, also considered as *indirect*, are used for calibration of power measurement such as *gold foil activation method* and *miniaturized neutron detector*. They require measurement of the *absolute thermal flux* at many points in the *core* which presents an inconvenient *(Yongqian, 1993).* More *power measurement* of *NRs* and *calibration techniques* can be found in *(Suzuki, 1966; Jalali et al., 2013).*

I.2.2 - Reactivity

The ρ *control* is an *important mean* to ensure the safety operation of *NRs*. ρ has been defined in terms of the deviation of the neutron multiplication from critical state. ρ means the relative change between the number of the previous generation neutrons n_1 and the next generation neutrons n_2. That is:

$$\rho = \frac{n_1 - n_2}{n_2} \tag{I.6}$$

The ρ worth developed in a *NR* can be affected by two different manners: by the motion of control rods (the action of the reactor control system, results in a power level change) considered as *extern factor*, or by many other *internal factors* which are usually, changes in *core* composition (*e.g., fuel depletion*), *poison*, and *changes* in *pressure* and in *temperature* of fuel, *moderator* and *coolant (Bhatt et al., 2013).* Hence, as represented on *Figure I.10*, the $\rho(t)$ of the system can be expressed as a sum of two contributions; external ρ and feedback ρ *(Duderstadt, Hamilton, 1976; Stacey, 2001).*

$$\rho(t) = \rho_{ext}(t) + \rho_f(t) \tag{I.7}$$

where $\rho_{ext}(t)$ represents the ρ due to the control rod motion and $\rho_f(t)$ represents the ρ feedback that is function of the reactor power level.

The ρ is measured with respect to the *steady state* (*nominal*) power level P^0 for which, as said before, $P = 0$, thus the system ρ can be written as:

$$\rho = \alpha_h \, \Delta h_{cr} + \alpha_m \left(T_m - T_m^0\right) + \alpha_f \left(T_f - T_f^0\right) \tag{I.8}$$

where T_m and T_f represent temperatures of the *moderator* and *fuel* respectively; T_m^0 and T_f^0 are their *stationary values*. The factor $\alpha_h \, \Delta h_{cr}$ represents the *external* ρ, $\rho_{ext,}$ and Δh_{cr} is the extraction length of a control rod measured from the critical position h_{cr}^0 and α_h is the rod worth coefficient.

$$\rho_{ext} = \alpha_h \Delta h_{cr}, \; \Delta h_{cr} = h_{cr} - h_{cr}^0 \tag{I.9}$$

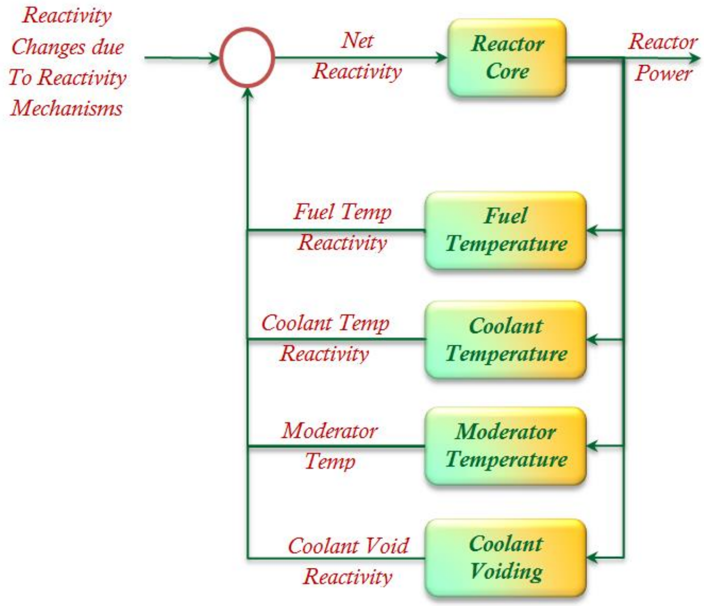


Figure I.10 - ρ as a function of reactor power.

The feedback term ρ_f represents the coupling term between the neutronics and thermal-hydraulics by means of the ρ feedback coefficients, *i.e.,* the fuel and moderator temperature coefficients, α_f and α_m, respectively. If the power of the reactor stays stable, the ρ summation of each factors should keep balance, that is ρ=0.
NRs must have sufficient excess ρ to compensate the negative ρ feedback effects such as those caused by the T_f and other factors such as power defects of ρ, fuel burnup, fission poisoning production, and also to allow full power operation for predetermined period of time. To compensate for the excess ρ, it is necessary to introduce an amount of negative ρ into the core which one can adjust or control it at will *(Mesquita, Souza, 2010).* The reactor control system must therefore continually adjust the ρ control mechanisms during a demanded power level change to keep the actual power changing at a rate that corresponds to the set-point change. But a positive feedback will tend to cause instability.

The ρ of the *NR* is a derived parameter usually cannot be directly measured. Determination of various ρs in *NR*s is usually performed by compensating the given ρ with the control rods to maintain the critical state. Calibration of control rod (determination of ρ worth per unit movement of control rod) is thus essential when the control rods are used as ρ standards to measure the ρ changes caused by any other perturbation in a reactor. Hence, the control rod worth measurement is a key point in reactor physics. It provides the reactor operator with a direct indication of net ρ, which is a much more definitive indication of the nuclear status of the core. It offers greater safety in reactor operation and aids the task of ρ management; therefore, it is strongly recommended as meter indication in the *Control Room*. Also, *periodic measurement* of ρ worth of control rods is one of the licensing requirements for any *NR*. Many countries however, already developed their own ρ measurement system.

The ρ should be computed with certain estimation soft-measuring methods, among them are the *inverse dynamic method*, *statistical method* and *neural network (NN) method.* Different *NNs* have been adopted to estimate the k_{eff} *(Jiang et al., 2008),* to calibrate control rod and predict axial power distribution *(Tyran et al., 1997),* and to identify ρ *(Fengyu et al., 2007).* In *(Ma et al., 2012),* the ρ of the *NR* is *estimated* by using a *combination* of *MLP network* and *mechanism model*.

I.2.3 - Temperature

Temperature is one of the operating conditions that affect the ρ of a reactor core. An increase in temperature will cause a decrease in the ρ. When reactor power changes, the temperatures of the various reactor components will change (*e.g.,* temperature of the fuel, coolant, and moderator will each rise). These temperature changes will alter one or more of the factors in the in the factor formula, resulting in ρ changes (*Figure I.10*).

At *TRIGA MARK II*, T_f were measured by three thermocouples in the center of the instrumented fuel element as shown on *Figure I.4*, which is the hottest position in the core. Fuel elements equipped with thermocouples are used to measure temperature inside fuel material. These instrumented fuel elements are clad with stainless steel and have the same dimensions of the standard fuel elements. Each instrumented fuel element is equipped with three chromel-alumel thermocouples, embedded along the vertical centerline of element. The sensitive tips of the three thermocouples are located one at the center of the fuel horizontal line and the other two 2.54 *cm* above and 2.54 *cm* below the center.

I.3 - Estimation of Heat Exchanger Parameters with Analytical Models

I.3.1 - Introduction

HEs (Ramesh, Dusan, 2003; Zapata et al., 2009; Bergman et al., 2011; Theodore, 2011; Rathakrishnan, 2012; Thulukkanam, 2013, Khentout et al., 2018) are widely used and play an important role in numerous industrial systems and processes *(Kakaç et al., 2012),* such as motor vehicles (*e.g., cars*, *trains*, *ships*), *air-conditioning systems*, *chemical* and *process industries (Persin et al., 2002),* Power plants *(Rathakrishnan, 2012), NRs (Laubscher, Dobson, 2013).*

The *HEs* are devices used to achieve continually efficient transfer heat (*i.e.*, maximum rate, and minimum investment and running costs) from one fluid to another that are at different temperatures, through an intermediate solid surface, without making them mix each other. the *HE* system used in the cooling circuit of the *NR* is provided for removing heat from the reactor core. The water is pumped through it and the heat is transferred from the hot to the cold fluid loop. It has highly *non-linearity* features in behavior where small changes in its operating condition may cause big changes in the dynamic performance. It is also a complex process caused not only by its *NL* dynamics but also by many phenomena such as *leakage*, *friction*, *temperature-dependent flow properties*, *contact resistance* and *unknown fluid properties*, the variable steady state gain and time constant with the process fluid *(Hanafi et al., 2011).* So, *HEs* can be difficult to control effectively *(Tan et al., 2009).*

Two special types of *HEs* commonly used in practice are condensers and boilers. *HEs* may be designed in many ways based on: the flow arrangement, construction type, transfer process, compactness and heat transfer mechanism *(Ramesh, Dusan, 2003; Kakaç et al., 2012; Rathakrishnan, 2012; Thulukkanam, 2013).* For flow arrangement, we can distinguish three main classes: (*a*) *co-current or parallel-flow* (*i.e.*, fluids flow in the same direction; (*b*) *counter-current or counter-flow* (*i.e.*, fluids flow in opposite direction); (*c*) *cross-flow* (*i.e.*, the direction of fluids is perpendicular to each other) *(Theodore, 2011*; *Kakaç et al., 2012*; *Rathakrishnan, 2012).* Each of these three types of *HEs* has advantages and drawbacks.

The shell-and-tube design is one of the popular *HE* types, which can be found in most process plants. It consists of series of tube bundle, which contain the fluid that must be either heated or cooled. The second fluid flows over the pipe in the shell side which can either supply or remove the heat. The tubes are usually kept with fixed and equal space between each other with baffles, which also force the shell-side fluid to flow across the shell to enhance the heat transfer (*Figure I.2*). This type of *HE* can be based on either co-current, countercurrent or cross-flow according to the flow directions and construction. The dynamic of the *HEs* can be described by laws of physics on mass, energy and momentum. By using those laws, a *HE* can be modeled with mathematical equations that depend on the FR, inlet and outlet temperatures of both streams that go through it. But, still, the HE is a process that cannot be modeled with a high accuracy. Usually, there are three well known classical mathematical methods, usually used for modeling a *HE*: the *Heat* (*thermal*) *Balance* (*HB*), the *Effectiveness - Number of Transfer Units* (*ε-NTU*) and the *Log-Mean Temperature Difference* (*LMTD*) methods *(Thulukkanam, 2013).* On the other hand, due to its accuracy, the *KF* is considered as the main estimation method applied to the linear state space model of the *HE*. Usually, for modeling of *HE*s the various parameters to be taken into account are *inlet* and *outlet* temperatures of *shell* and *tube* side fluids, and their *FR*s *(Mandavgane, Pandharipande, 2006).*

When the *HEs* are in use, their performances deteriorate continually. Indeed, they are always vulnerable to degradations which are non-periodic and non-stationary processes, and depend upon the variation of their internal coefficients vs. time. Among these impoverishments, the occurring of fouling *(Theodore, 2011; Rathakrishnan, 2012; Thulukkanam, 2013)* on the heat transfer surface. So, the metal that separates the hot and cold fluids in the *HE*: (*a*) accumulates deposits from the fluids, (*b*) creates biofilm and (*c*) starts to corrode. Indeed, *fouling* is very complicated phenomenon which tends to increase over time. It can be categorized into particles, corrosion, biological, crystallization, chemical reaction and freeze. As consequence of fouling accumulates, the decrease of the *overall heat transfer coefficient*, significant increase in *pressure* and *restricts* the *FR* which influence negatively on *heat exchange efficiency* and finally will increase the thermal load, energy and maintenance costs *(Kakaç et al., 2012; Thulukkanam, 2013).* Most of the *fouling prediction* models reported in literature are based on the operating conditions and they do not depend on the properties of the fluid being processed *(Biyanto et al., 2007).* So, it is necessary to assess periodically the *HE* performance by measuring their thermal hydraulic parameters, to know its health and follow its dynamic state evolution, in order to maintain it at high efficiency level.

I.3.2 - Heat Balance

From physics approach in a system where steady state heat transfer occurs, such as in a *HE*, the *HB* methods will take place. The *heat transfer rate* (*HTR*) or the thermal power in this case is given by *(Bergman et al., 2011; Borkar et al., 2014)* :

$$\dot{Q}_n = \dot{m}_n c_{pn} \Delta T_n \quad \text{(I.10)}$$

where the subscript n indicates either the *hot* or *cold* stream; $\dot{m}_n$ is the *MFR* of the *fluid n;* and c_{pn} is the *specific heat* of the fluid n. ΔT_n represents the difference between the temperatures at the *inlet* and the *outlet* of both fluids.

$$\Delta T_h = T_{hi} - T_{ho}, \quad \text{(I.11}a\text{)}$$

$$\Delta T_c = T_{co} - T_{ci} \quad \text{(I.11}b\text{)}$$

Equation I.10 is independent of the flow arrangement and the *HE* type.
The product of c_{pn} and T_{ni} (or T_{no}) is the *inlet* (or *outlet*) *enthalpy* of the fluid n. The product of $\dot{m}_n$ by c_{pn}, is the *heat capacity* or *heat specific capacity,* C_n:

$$C_n = \dot{m}_n c_{pn} \quad \text{(I.12)}$$

So, *Equation I.10* will be written as:

$$\dot{Q}_n = C_n \Delta T_n \quad \text{(I.13)}$$

with T_{hi} and T_{ho} are the *temperature* of the *hot* fluid entering and exiting the inside *pipe/tube,* respectively; T_{ci} and T_{co} are the *temperature* of the *cold* fluid entering and exiting the *annulus* respectively.
Therefore, *Equation I.13* can be developed into two separated equations for both *hot* and *cold* fluids, $\dot{Q}_h$ and $\dot{Q}_c$ which are, respectively, the *HTRs* transmit from the hot fluid and received by the cold fluid.

$$\dot{Q}_h = \dot{m}_h\, c_{ph}\, \Delta T_h \tag{I.14a}$$

$$\dot{Q}_c = \dot{m}_c\, c_{pc}\, \Delta T_c \tag{I.14b}$$

The traditional *HB* model is used based on the assumption that the *HE* is isolated which means no losses, the amount of heat given up by the hot fluid is equal to the amount of heat received by the cold fluid (notion of *heat conservation*).
If a *HE* is well insulated, $\dot{Q}_h$ and $\dot{Q}_c$ should be equal. Then the heat lost by the hot fluid is gained by the cold fluid ($\dot{Q}_h = \dot{Q}_c$). Therefore, from *Equations I.14a* and *b*, we get:

$$\dot{Q}_h = \dot{Q}_c = C_h\,\Delta T_h = C_c\,\Delta T_c \tag{I.15}$$

In practice, $\dot{Q}_h$ and $\dot{Q}_c$ differ due to heat losses or gains to/from the environment. Practically, the thermic statement allows the calculation of the *thermal power* of given up ($\dot{Q}_h$), received or gained ($\dot{Q}_c$) and lost ($\Delta\dot{Q}$) in a *HE*.

$$\dot{Q}_h = \dot{Q}_c + \Delta\dot{Q} \tag{I.16}$$

At steady state, usually $\Delta\dot{Q}$ in *Equation I.16* is proportional to $\dot{Q}_c$. So, the *thermal power ratio* defined as:

$$R = \frac{\dot{Q}_h}{\dot{Q}_c} = \frac{C_h}{C_c}\frac{\Delta T_h}{\Delta T_c} \tag{I.17}$$

is almost constant as appears on *Figure V.4*, in *experimental part (Chapter V).* The ratio $\Delta T_c / \Delta T_h$ is the *effectiveness* of the *HE* and its inverse is the *capacity ratio* or the *balanced flow* *(Narayanan, Venkatarathnam, 1999; Borkar et al., 2014).*
In the case of our *HE*, the *hot* and *cold* fluids are the same, light water *(i.e.,* $c_{ph} = c_{pc} = c_p$), so *Equation I.17* will be reduced to:

$$R = \dot{m}_h\,\Delta T_h \;/\; (\dot{m}_c\,\Delta T_c) \tag{I.18}$$

We can find from this equation (*Equation I.18*) :

$$\Delta T_h = R\,(\dot{m}_c \;/\; \dot{m}_h)\,\Delta T_c \tag{I.19a}$$

and

$$\Delta T_c = (1/R)\,(\dot{m}_h \;/\; \dot{m}_c)\,\Delta T_h \tag{I.19b}$$

I.3.2.1 - Temperatures Estimation

If we consider the ratio *R* as known constant, the estimation of different temperatures of a *HE* can be found from *Equations I.19a* or *I.19b* as:

$$\hat{T}_{hi} = T_{ho} + R\,\frac{C_c}{C_h}\,\Delta T_c \tag{I.20a}$$

$$\hat{T}_{ho} = T_{hi} - R\frac{C_c}{C_h}\Delta T_c \quad (I.20b)$$

$$\hat{T}_{ci} = T_{co} - \frac{1}{R}\frac{C_h}{C_c}\Delta T_h \quad (I.20c)$$

$$\hat{T}_{co} = T_{ci} + \frac{1}{R}\frac{C_h}{C_c}\Delta T_h \quad (I.20d)$$

I.3.2.1 - Mass Flow Rate Estimation

For the estimation of the *MFRs* at both fluids of a *HE*, we can also use *Equation I.19a* or *b*, and we find:

$$\hat{\dot{m}}_h = R\frac{c_{pc}}{c_{ph}}\frac{\Delta T_c}{\Delta T_h}\dot{m}_c \quad (I.21a)$$

and

$$\hat{\dot{m}}_c = \frac{1}{R}\frac{c_{ph}}{c_{pc}}\frac{\Delta T_h}{\Delta T_c}\dot{m}_h \quad (I.21b)$$

We note in this method that the prediction of one among the six parameters of the *HE* (*i.e.*, T_{hi}, T_{ho}, T_{ci}, T_{co}, $\dot{m}_h$, $\dot{m}_c$) requires the availability of the *measurements* of all *other parameters.*

I.3.3 - Effectiveness - Number of Transfer Units

The *effectiveness - number of transfer units (ε-NTU)* method is based on the notion of the *effectiveness* (*efficiency*), ε, of the *HE* *(Ramesh, Dusan, 2003; Yunus et al., 2004; Theodore, 2011).*

$$\varepsilon = \frac{\dot{Q}_n}{\dot{Q}_{max}} \quad (I.22)$$

where $\dot{Q}$ and $\dot{Q}_{max}$ are, respectively, the *actual* and *maximum possible HTRs*, and $\dot{Q}_{max}$ is given by:

$$\dot{Q}_{max} = C_{min}\,\Delta T_{max} \quad (I.23)$$

were C_{min} is the smallest of *heat capacities*; C_h and C_c. $\Delta T_{max,}$ is the *maximum temperature difference* in the *HE.* It is defined as the difference between *inlet* temperatures of *hot* and *cold fluids (Ramesh, Dusan, 2003; Yunus et al., 2004).* ε depends on the *HE geometry,* flow arrangement and the *number of transfer units, NTU*, defined as *(Ramesh, Dusan, 2003; Theodore, 2011)* :

$$NTU = \frac{UA}{C_{min}} \quad (I.24)$$

By using *Equations I.10* and *I.23*, *Equation I.22* will be:

$$\varepsilon_n = \frac{C_n}{C_{min}} \frac{\Delta T_n}{\Delta T_{max}} \tag{I.25}$$

So, ε_n, is determined using the *inlet* and *outlet* temperatures as well as the *heat capacities*, C_n and C_{min}.
Both fluids (*i.e., hot* and *cold*) of the *HE* are considered the same, light water (*i.e.,* $cp_h = cp_c = cp$) as given in *Table I.1*, and since $\dot{m}_c$ is less than $\dot{m}_h$, as shown on *Figure V.2*, so we get $C_{min} = C_c$.
Usually, the ε_n will be *different* at *hot* and *cold* fluids of the *HE*. We have $\Delta T_{max} = T_{hi} - T_{ci}$ as shown by *Figure I.1.* Hence, *Equation I.25* will be developed in two equations (*Narayanan, Venkatarathnam, 1999; Theodore, 2011*) :

$$\varepsilon_h = \frac{C_h}{C_c} \frac{T_{hi} - T_{ho}}{T_{hi} - T_{ci}} \tag{I.26a}$$

and

$$\varepsilon_c = \frac{T_{co} - T_{ci}}{T_{hi} - T_{ci}} \tag{I.26b}$$

I.3.3.1 - Temperatures Estimation

If we consider ε_h and ε_c in the equations above as known, found by calibration as shown in experiment part (*Chapter V*), the *inlet temperatures*, $\hat{T}_{hi}$ and $\hat{T}_{ci}$, can be estimated from both *Equations 26a* and *26b*. Therefore, there are two formulas for estimation of both of these temperatures.
From the same equations (*i.e., Equations 17a* and *17b*), we can also obtain, respectively, the *outlet temperatures* estimation, $\hat{T}_{ho}$ and $\hat{T}_{co}$.
Finally, we get:

$$\hat{T}_{hi} = \frac{1}{1 - \varepsilon_h \frac{C_c}{C_h}} T_{ho} - \frac{\varepsilon_h \frac{C_c}{C_h}}{1 - \varepsilon_h \frac{C_c}{C_h}} T_{ci} \tag{I.27a}$$

or

$$\hat{T}_{hi} = \varepsilon_c\, T_{co} - \varepsilon_c\, (1 - \varepsilon_c)\, T_{ci}; \tag{I.27b}$$

$$\hat{T}_{ho} = (1 - \varepsilon_h \frac{C_c}{C_h})\, T_{hi} + \varepsilon_h \frac{C_c}{C_h}\, T_{ci}, \tag{I.27c}$$

$$\hat{T}_{ci} = - \frac{\varepsilon_c}{1 - \varepsilon_c} T_{hi} + \frac{1}{1 - \varepsilon_c} T_{co}; \tag{I.27d}$$

or

$$\hat{T}_{ci} = - \frac{1 - \varepsilon_h \frac{C_c}{C_h}}{\varepsilon_h \frac{C_c}{C_h}} T_{hi} + \frac{1}{\varepsilon_h \frac{C_c}{C_h}} T_{ho}, \tag{I.27e}$$

$$\hat{T}_{co} = (1 - \varepsilon_c)\, T_{ci} + \varepsilon_c T_{hi}. \tag{I.27f}$$

We not that the estimation of the *inlet temperature* of one fluid depends on the *inlet temperature* of the other fluid and an *outlet temperature* of one fluid. Moreover, the estimation of the *outlet temperature* of each fluid depends on both *inlet temperatures*.

I.3.3.2 - Mass Flow Rate Estimation

From *Equation I.26a* we can also calculate the estimation of the *MFRs* ($\dot{m}_h$ and $\dot{m}_c$) as follow:

$$\widehat{\dot{m}}_h = \varepsilon_h \frac{T_{hi}-T_{ci}}{T_{hi}-T_{ho}} \dot{m}_c \tag{I.28a}$$

and

$$\widehat{\dot{m}}_c = [1/(\varepsilon_h \frac{T_{hi}-T_{ci}}{T_{hi}-T_{ho}})]\, \dot{m}_h \tag{I.28b}$$

From these equations, we note that the estimation of the *MFRs* of both fluids is independent of T_{co}.

I.3.4 - Temperatures estimation with LMTD

The temperature changes between two fluids across a *HE* can be represented by the *LMTD.* This relation developed earlier is limited only to the *co-current* and *counter-current HE*s. Later, similar relations are also developed for the *cross-flow* and *multi-pass shell-and-tube HE*s *(Yunus et al., 2004; Theodore, 2011).*

$$\Delta T_{LMTD} = \frac{\Delta T_1 - \Delta T_2}{\ln(\frac{\Delta T_1}{\Delta T_2})} = \frac{\Delta T_2 - \Delta T_1}{\ln(\frac{\Delta T_2}{\Delta T_1})} \tag{I.29}$$

where ΔT_1 and ΔT_2 represent the temperature difference at each end of the *HE*.
For a *co-current:* $\Delta T_1 = T_{hi} - T_{ci}$ and $\Delta T_2 = T_{ho} - T_{co}$. For a *counter-current:* $\Delta T_1 = T_{hi} - T_{co}$ and $\Delta T_2 = T_{ho} - T_{ci}$ *(Bergman et al., 2011).*
Note that, for the same inlet and outlet temperatures, the *LMTD* for *counter-current* exceeds that for *co-current*. Hence the surface area required to affect prescribed *heat transfer rate* $\dot{Q}$ is smaller for the *counter-current* than for the *co-current* arrangement, assuming the same value of *U*. Also note that T_{co} can exceed T_{ho} for *counter-current* but not for *co-current*.
From energy conservation given by *Equation I.15,* the *HTR* for *a co-current* and *counter-current HE* in steady state may relate to ΔT_{LMTD} by means of:

$$\dot{Q} = U A\, \Delta T_{LMTD} \tag{I.30}$$

where *U* is the *Overall heat transfer coefficient* and *A* is the *Heat Transfer surface* area which separates the two fluids.

In the beginning, suppose: $B_h = \frac{1}{C_h}$ and $B_c = \frac{1}{C_c}$.

By tacking in consideration the loss of the *HTR* as given by *Equation I.17*, *Equation I.29* for a *co-current HE*, can be rearranged as:

$$ln\,(\frac{\Delta T_2}{\Delta T_1}) = -\,(B_h + \frac{B_c}{R})\; UA \tag{I.31}$$

From this equation, the *outlet temperatures* of both fluids will be expressed as:

$$T_{ho} = (T_{hi} - T_{ci})\ exp\ [-\ (B_h + \frac{B_c}{R})\ ]\ UA + T_{co} \tag{I.32a}$$

$$T_{co} = -\ (T_{hi} - T_{ci})\ exp\ [-\ (B_h - \frac{B_c}{R})\ ]\ UA + T_{ho} \tag{I.32b}$$

For a *counter-current HE*, *Equation I.31* corresponds to:

$$ln\ (\frac{\Delta T_2}{\Delta T_1}) = -\ (B_h + \frac{B_c}{R})\ UA \tag{I.33}$$

and the *outlet temperatures* of both fluids will be expressed as:

$$T_{ho} = (T_{hi} - T_{co})\ exp\ [-\ (B_h - \frac{B_c}{R})\ ]\ UA + T_{ci} \tag{I.34a}$$

$$T_{co} = -\ (T_{ho} - T_{ci})\ exp\ [+(B_h - \frac{B_c}{R})\ ]\ UA + T_{hi} \tag{I.34b}$$

For a *co-current* and *counter-current based shell-and-tube HE*, the outlet temperatures will be expressed, respectively, by the same formula as in *Equations I.32a* and *b* and *Equations I.34a* and *b*, except a multiplication of ΔT_{LMTD} by the *correction factor*, *Fc*. This factor can be calculated from abacus (*Yunus et al., 2004*), or experiment as shown on *Figure V.6*. We note in *Equations I.29* and *I.31* that the estimation of one *outlet temperature*, T_{ho} or T_{co}, requires the measurement of all other parameters. We mention that these *outlet temperatures* can be expressed also function of only the *inlet temperatures* and *FRs* (*Theodore, 2011*).

I.3.5 - Combined Method

With the concept of utilizing the advantage of each method, the combined method (*CMd*) can enhance performance and meet more desirable characteristics.

As illustrated on *Figure I.11*, the idea of the estimation by *CMd* is to take for each discrete time, *k*, the best estimation among, $\hat{E}_1$ - $\hat{E}_m$, provided by the used methods, *i.e.*, the *HB*, the ε-*NTU*, and the *LMTD*. This is done by selecting the optimal estimation, $\hat{E}_{opt}$ that accompanying by minimum value of the *Maximum Absolute Error* (*MAE*) of the estimation, noted *mAE*.

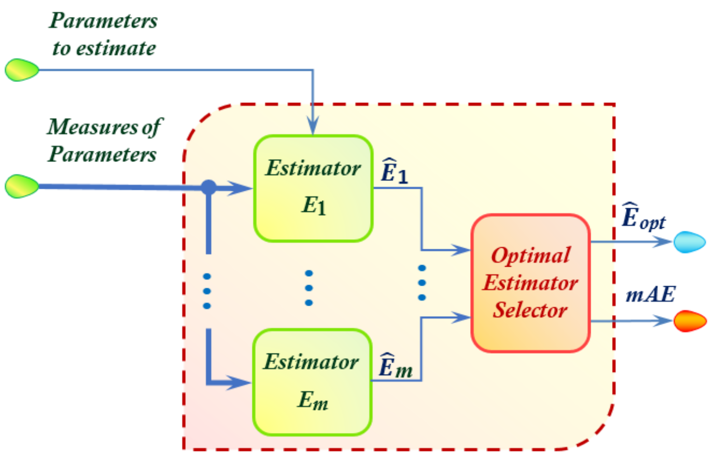


Figure I.11 - Bloc diagram of the estimation by using methods combination approach.

I.3.6 - Kalman Filter

In this part, we apply the *KF* to estimate the *HE outlet temperatures* using *Linear State Equations* (*LSEs*). To do this, first we start with the *KF* theory, then we present the *LSE* of the *HE* and finally, we estimate the *outlet temperatures* of the latest.

I.3.6.1 - Kalman Filter Theory

State estimation technique by the *KF* is developed in around the year 1960 *(Kalman, Bucy, 1960)* for the *LSs* and now it is proved to be more advantageous than other approaches. The *KF* is recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimation of the current state.
For dynamic systems described by state space models, more development in *FDe* schemes has relied on the system being linear, and the noise and disturbances *(Isermann, Ballé, 1997; Olivier-Maget, 2007)* being Gaussian. In such cases, the *KF* is usually used for state estimation and output prediction. The predicted output is then compared with the actual output measurement and the result from the comparison, *innovation,* is used as residual for the *FDe*. Then the *FDi* is restricted to the analysis of the *innovation* signal.

As shown on *Figure I.12,* the *KF* includes two *models* (*equations*), *process* (*evolution*) *model* and an *observation* (*measurement*) *model*. They are given, consecutively, by *Equations I.35* and *I.36* below *(Hanlon, Maybeck, 2000; Venkatasubramanian et al., 2003a; Olivier-Maget, 2007).*
First, we start with the *process model*:

$$x_k = F_k\, x_{k-1} + G_k\, u_k + w_k \tag{I.35}$$

where: (*a*) $x_k \in \Re^{(nx\times 1)}$ represents the n_x *state estimation* that we try to reach at the *present* time step, *k,* with $\Re^{(a\times b)}$ represents real values matrix of $a\times b$ dimension. x_{k-1} represents the *estimated state* at the *previous* time step, *k*-1. The subscript *k* indicates that *x* depends on it. (*b*) $F_k \in \Re^{(nx\times nx)}$ is the *state transition matrix* of the system which links the previous state *k*-1 with the current state *k*. (*c*) $w_k \in \Re^{(nx\times 1)}$ is the *model* (*system*) *noise* which is zero-mean white *Gaussian* ($E[w_k] = 0$, where E[.] denotes the *expectation*) of known positive *covariance matrix* $Q_k \in \Re^{(nx\times nx)}$, so $E[w_i w_j^T] = Q_k \delta_{ij}$, where δ_{ij} denotes the *Kronecker delta function*). (*d*) $u_k \in \Re^{(nu\times 1)}$ represents the *nu* applied commands to the process which is known but accompanying by a control noise w_k. (*e*) $G_k \in \Re^{(nx\times nu)}$ is a *control matrix* applied to the *command vector* u_k which links the command input u_k with the state x_k.

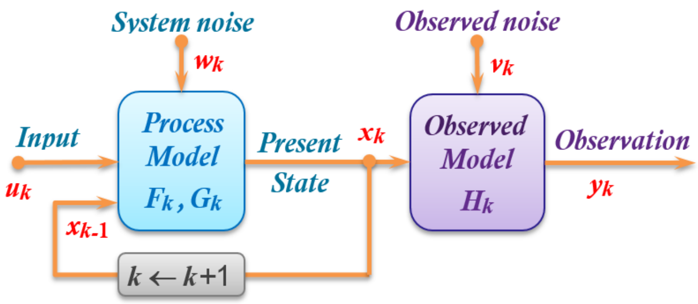


Figure I.12 - Synoptic of the LS as is seen by the KF.

Second, due to the noise, the *observation*, given by the following equation, intervenes to resolve the *process equation* by using the measurement and know exactly *x*.

$$y_k = H_k\, x_k + v_k \tag{I.36}$$

where: (*a*) $y_k \in \Re^{(nx\times1)}$ represents the *ny observations* (*measurements* or *observations*) of process at time *k*. (*b*) $H_k \in \Re^{(ny\times nx)}$ is an *output* (*measurement* or *observation*) *sensitivity matrix*. It maps the estimated state space x_k into the observed space y_k. (*c*) $v_k \in \Re^{(nx\times1)}$ is the *measurement noise* which is zero-mean white *Gaussian* ($E[v_i] = 0$) of known positive *covariance matrix* $R_k \in \Re^{(ny\times ny)}$ ($E[v_i v_j^T] = R_k \delta_{ij}$).

It is important to mention that there is no correlation between the *model noise* w_k and the *measurement noise* v_k. They are assumed *independent* ($w_i \perp v_j$, *i.e.,* $E[w_i v_j^T] = 0, \forall i, j$).

The *optimum Kalman Filtering* for linear dynamic systems requires an exact knowledge of the *process noise covariance matrix,* Q_k, and the *measurement noise covariance matrix,* R_k. These matrices are considered as adjusting tools of the *KF because* they influence the calculation of the *gain*, and so the *convergence* of the filter.

The *KF* dynamic results from recursive equations cycles of *a priori* (*prediction* or *time update*) based on physical model and *a posteriori* (*correction*, *filtering* or *measurement update*), as shown on *Figure I.13*, in which comparison between prediction and measurement is done. It *propagates* the *mean* and *covariance* of the *probability distribution function* of the model state in an *optimal* way with *minimization* of the *MSE*. However, the *KF* requires the knowledge of all the system and noise parameters.

As shown on *Figure I.13*, the *first phase* of an estimation with the *KF* is the *prediction* which uses the estimated state from the *previous time*, *k*-1, to produce an estimation of the state at the *present time, k*.

$$\hat{x}_k^- = F_k \hat{x}_{k-1}^+ + G_k u_k \tag{I.37}$$

The *covariance matrix,* $P_k \in \Re^{(nx\times nx)}$, is defined as:

$$P_k = cov[e_k] = E[e_k e_k^T] \tag{I.38}$$

with *cov* [.] represents the *covariance* and e_k is the *estimation error* defined as the difference between the state value and its estimation:

$$e_k = x_k - \hat{x}_k \tag{I.39}$$

Therefore, the *predicted covariance matrix* will be:

$$P_k^- = F_k P_{k-1}^+ F_k^T + Q_k \tag{I.40}$$

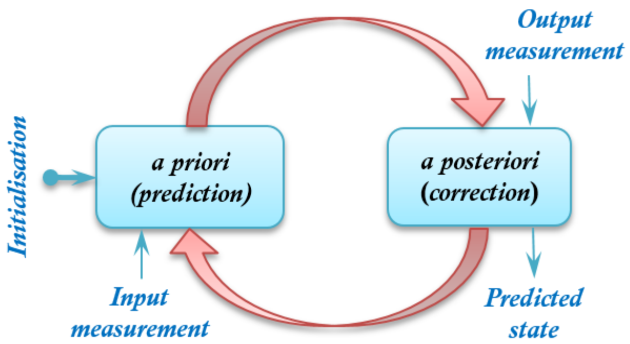


Figure I.13 - Steps of the KF.

The *second phase* of the estimation with the *KF* is the *correction* where the observations, y_k, at the present time *k* is combined with the predicted state $\hat{x}_k^-$ with the aim of obtaining more precise estimation $\hat{x}_k^+$:

$$\hat{x}_k^+ = \hat{x}_k^- + K_k r_k \tag{I.41}$$

where the term r_k is called the *KF innovation vector*:

$$r_k = y_k - H_k\, \hat{x}_k^- \tag{I.42}$$

and $K_k \in \Re^{(nx \times ny)}$ is the *optimal Kalman gain*:

$$K_k = P_k^- H_k^T S_k^{-1} \tag{I.43}$$

where $S_k \in \Re^{(nx \times ny)}$, is the *KF error* or *innovation covariance matrix*:

$$S_k = H_k P_k^- H_k^T + R_k \tag{I.44}$$

and P_k^- is the associated *predicted covariance matrix.* It is *updated* using:

$$P_k^+ = (I - K_k H_k)\, P_k^- \tag{I.45}$$

Finally, the output estimation will be:

$$\hat{y}_k = H_k \hat{x}_k^+ \tag{I.46}$$

The *initial state, x_0,* is *normally distributed* with zero *mean* and *covariance P_0*. By introducing these initial conditions ($x_0 = \hat{x}_0^+$ and $P_0 = P_0^+$), supposed known previously, the *KF* operation can be represented as given on *Figure I.14*.

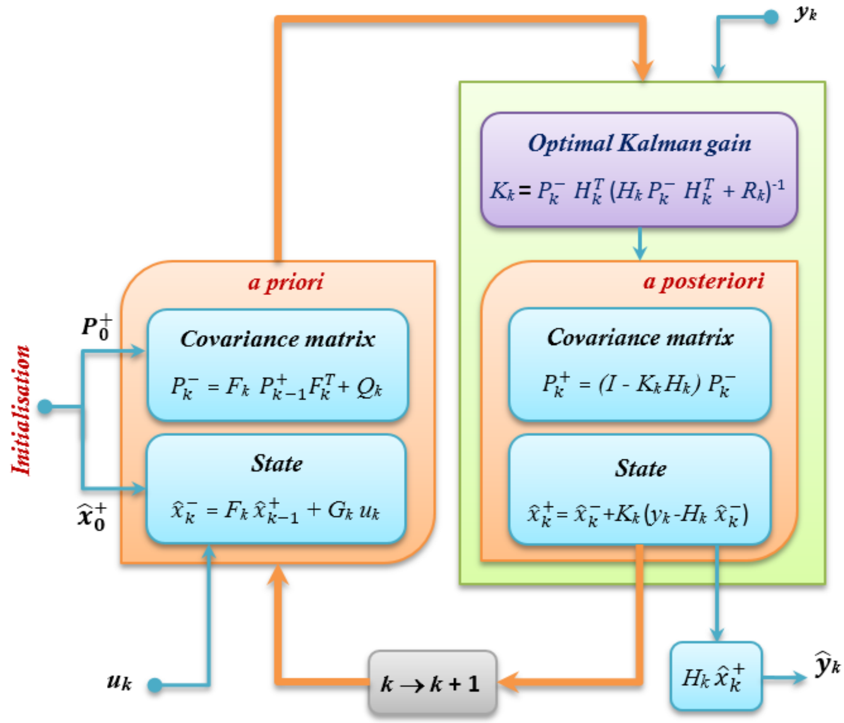


Figure I.14 - KF loop.

When a *HE* is considered as a system *time invariant*, consequently its coefficients *F, G* and *H* are *constant*, independent of the time step *k*, and *system equations* given by *Equations I.35* and *I.36* can be rewritten as:

$$x_k = F\, x_{k-1} + G\, u_k + w_k \tag{I.47a}$$

$$y_k = H\, x_k + v_k \tag{I.47b}$$

We note that in some references, instead of the notation A_k^- and A_k^+, they use $A_{k|k-1}$ and $A_{k|k}$, where *A* can be the *state estimation,* $\hat{x}$, or the *covariance matrix, P*.

I.3.6.2 - Linear State Equation of the Heat Exchanger

As mentioned above for *ε-NTU* method, the *LSE* approach can be used even when measurements of some variables are not available. For instance, when the outlet temperatures of the cold and hot fluid streams in a specified *HE* are not available, this method can be used to predict them.

Usually, for modeling the dynamic of a *HE*, we find *two* main *approaches*: *distributed* and *lumped* Varbanov et al., 2011). Depending on the application, either approach may be the most suitable, but the *lumped cell-based model* remains more popular. In this case, the system dynamic is obtained through a *HB* rule applied to every element of the *lumped* model.

In this paper, a *counter-current HE* is modeled in the form of *one cell* (*Figure I.15*), four temperature parameters, two states (*hot* and *cold*), single element per fluid and exchanging heat only with each other through a separating wall.

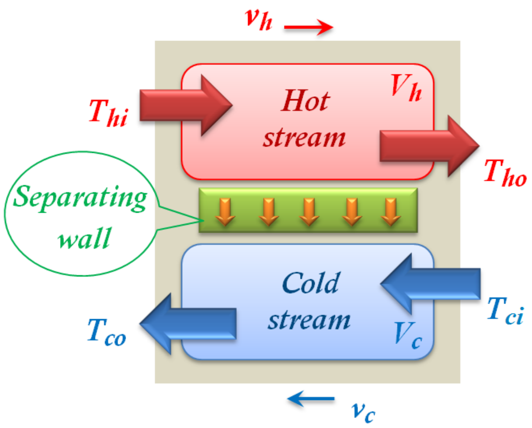


Figure I.15 - A single-cell lumped model representation of counter-current HE.

The hot fluid enters the *cell* at the temperature T_{hi} and leaves at T_{ho} with a *velocity* v_h, whereas the cold fluid enters at T_{ci} and leaves at T_{co} with a *velocity* v_c. The fluid volume in the hot and cold streams are V_h and V_c, respectively.

In this work, the *Mathematical Model* (*MM*) of the *HE* is based on certain assumptions Gudmundssonet al., 2009; Varbanov et al., 2011) : (*a*) The wall thermal resistance to the heat transfer is negligible; (*b*) The *HE* is perfectly insulated, which means the heat losses to the surroundings is negligible; (*c*) The heat conduction along the axial direction of the fluid flow is negligible; both within the fluid and within the wall; (*d*) All thermal properties are constant.

According to the assumptions that the coefficients A_h, A_c, c_{ph}, c_{pc}, ρ_h, ρ_c, V_h and V_c are *known*, *constant* and *positive*. A *single cell* of a *co-current* or *counter-current HE*, as represented by *Figure I.15*, gives rise to simplified *second order* dynamic *differential equation* (Rahman, Devanathan, 1994; Narayanan, Venkatarathnam, 1999; Zapata et al., 2009; Hanafi et al., 2011) :

$$\frac{dT_{ho}}{dt} = \frac{v_h}{V_h}(T_{hi} - T_{ho}) - \frac{U_h A_h}{c_{ph}\rho_h V_h}(T_{ho} - T_{co}) \quad (I.48a)$$

$$\frac{dT_{co}}{dt} = \frac{v_c}{V_c}(T_{ci} - T_{co}) + \frac{U_c A_c}{c_{pc}\rho_c V_c}(T_{ho} - T_{co}) \quad (I.48b)$$

For a *shell-and-tube HE* (Rahman, Devanathan, 1994; Hanafi et al., 2011) and a *cross-flow* (Gudmundssonet al., 2009), it is necessary to introduce a *correction factor, Fc,* (Blanke et al., 2001; Gudmundssonet al., 2009; Theodore, 2011; Rathakrishnan, 2012; Borkar et al., 2014) in *Equations I.48a* and *I.48b* by multiply it with U_n. The value of this factor

is less than or equal to 1 and takes into account the specificity and the geometry of the *shell-and-tube HE*, the inlet and outlet temperatures of the hot and cold streams.
After introducing *Fc* in *Equations 39a* and *b*, we put the following constants:

$$k_h = U_h\, A_h\, F_c / [cp_h\, \rho_h\, V_h];\; k_c = U_c\, A_c\, F_c / [cp_c \rho_c V_c] \tag{I.49a}$$

$$r_h = v_h \;/\; V_h\, ;\, r_c = v_c \;/\; V_c \tag{I.49b}$$

Then, the model given by *Equations I.39a* and *b* can be rewritten in the following form:

$$\frac{dT_{ho}}{dt} = r_h\,(T_{hi} - T_{ho}) - k_h\,(T_{ho} - T_{co}) \tag{I.50a}$$

$$\frac{dT_{co}}{dt} = r_c(T_{ci} - T_{co}) + k_h\,(T_{ho} - T_{co}) \tag{I.50b}$$

It is worth mentioning that if the *heat transfer coefficient*, *U*, is assumed depends on temperatures of the fluids, model of *Equations* I.50*a* and *b* will be *NL*.
Rearrange the two above equations, we find:

$$\begin{Bmatrix} \frac{dTh_O}{dt} \\ \frac{dTc_O}{dt} \end{Bmatrix} = \begin{Bmatrix} -(r_h + k_h) & k_h \\ k_c & -(r_c + k_c) \end{Bmatrix} \times \begin{Bmatrix} T_{ho} \\ T_{co} \end{Bmatrix} + \begin{Bmatrix} r_h & 0 \\ 0 & r_c \end{Bmatrix} \times \begin{Bmatrix} T_{hi} \\ T_{ci} \end{Bmatrix} \tag{I.51a}$$

$$\begin{Bmatrix} T_{ho} \\ T_{co} \end{Bmatrix} = \begin{Bmatrix} 1 & 0 \\ 0 & 1 \end{Bmatrix} \times \begin{Bmatrix} T_{ho} \\ T_{co} \end{Bmatrix} \tag{I.51b}$$

Moreover, we consider the following hypothesis: the *state vector*, $(x_1,\, x_2) = (T_{ho},\, T_{co})$; the *input vector*, $(u_1,\, u_2) = (T_{hi},\, T_{ci})$ and the *output vector*, $(y_1,\, y_2) = (T_{ho},\, T_{co})$. So, the *state equation* given by the above equations can be rewritten as:

$$\begin{Bmatrix} \frac{dx_1}{dt} \\ \frac{dx_2}{dt} \end{Bmatrix} = \begin{Bmatrix} -(r_h + k_h) & k_h \\ k_c & -(r_c + k_c) \end{Bmatrix} \times \begin{Bmatrix} x_1 \\ x_2 \end{Bmatrix} + \begin{Bmatrix} r_h & 0 \\ 0 & r_c \end{Bmatrix} \times \begin{Bmatrix} u_1 \\ u_2 \end{Bmatrix} \tag{I.52a}$$

$$\begin{Bmatrix} y_1 \\ y_2 \end{Bmatrix} = \begin{Bmatrix} 1 & 0 \\ 0 & 1 \end{Bmatrix} \times \begin{Bmatrix} x_1 \\ x_2 \end{Bmatrix} \tag{I.52b}$$

3.6.2.3 - Outlet Temperatures Estimation of the Heat Exchanger

In this part of work, the aim is to use the *KF* to estimate *outlet temperatures* at both streams of the *HE*. To do this, we used *MATLAB Simulink* for implementation, as illustrated on the three following *Figures* (*Figures I.16-I.18*).

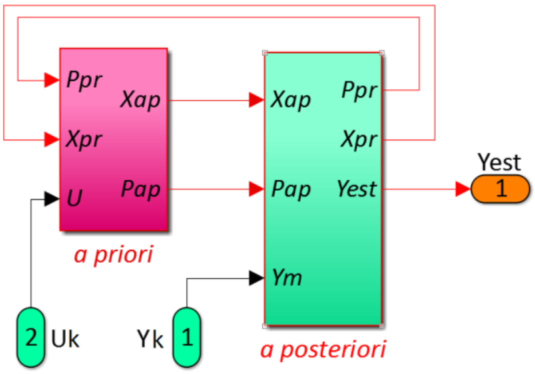


Figure I.16 - Simulink implementation of the KF estimator of the HE. (Inputs: U, Ym are respectively the input and measurement data. Outputs: Yest is the estimated output. Internal: Xap, Ppr, Xpr, Pap are respectively a priori state, a priori covariance matrix, a posteriori state and a posteriori covariance matrix).

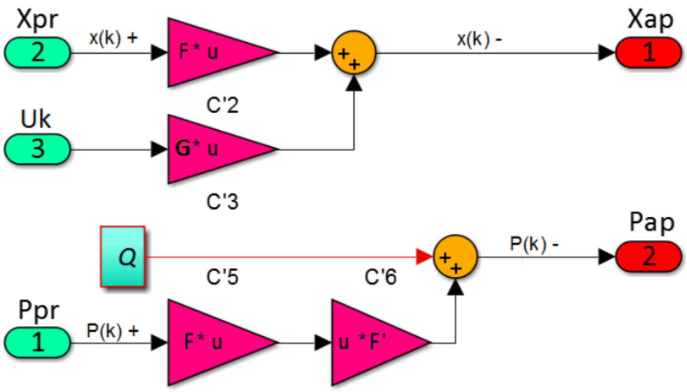


Figure I.17 - Simulink implementation of "a priori" bloc of Figure I.16.

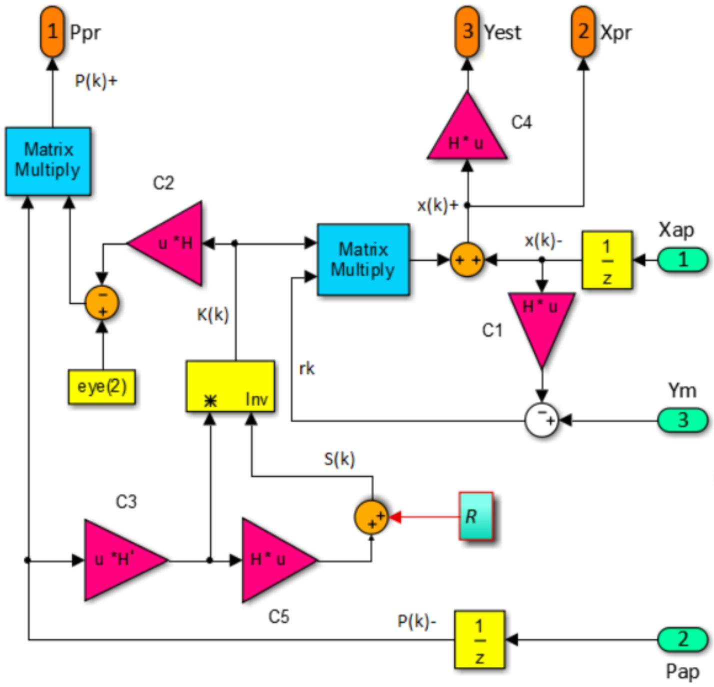


Figure I.18 - Simulink implementation of "a posteriori" bloc of Figure I.16.

I.3.7 - Estimation Performances

The performances of the models were assessed through statistical validity by using the *Correlation Coefficient (CC)* and the means square error. For *SFA* purposes, the following classic parameters for the estimation error are instead evaluated.
MEE, represent the *mean* of the *estimation error* sequence after the sensor accommodation (triggering of AE).

$$MEE = \frac{1}{N}\sum_{k=1}^{N} \left(y(k) - \hat{y}(k)\right) \qquad (I.53)$$

where y is the actual value, $\hat{y}$ is the predicted value and N refers to the number of observations.
VEE represent the *variance* of the *estimation error* sequence after the sensor accommodation (triggering of *AE*).

$$VEE = \frac{1}{N}\sum_{k=1}^{N} \left[\left(y(k) - \hat{y}(k)\right) - MEE\right]^2 \qquad (I.54)$$

MEE and *VEE* measure the effectiveness of approximation in reproducing the physical parameter at nominal conditions *(Campa et al., 2002b).*
The *RMSE* is defined as *(Biyanto et al., 2007)* :

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{\left(Y_i - \hat{Y}_i\right)^2}{N}} \qquad (I.55)$$

The performance of estimation based on model is measured in terms of the *RMSE*. The thresholds are determined based on the prediction performance. In order to limit the *false detection* rate, the thresholds are set as *(Uluyola et al., 2001)* :

$$\tau_i = \alpha\ RMSE_i \text{ where the coefficient } \alpha > 1 \qquad (I.56)$$

Mean Absolute percentage error (*MAPE*) calculated for the *worse case* and is used as metrics to assess accuracy of *prediction*. It is conservatively defined by the *largest absolute percent error* as *(Mattern, Jaw, 1998)* :

$$MAPE = \frac{\text{MAE}}{\text{y}} \times 100\% \qquad (I.57)$$

The *error* corresponds to the point y where the worst-case error was happened.
Furthermore, the *estimation performance* includes: *mean detection time*, number of *undetected faults* (*UD*), *number of False Alarms* (*FAl*).

I.4 - Conclusion

In this chapter we started by a general description of *TRIGA MARK II NRR* including mainly the core, the cooling circuits and *DAS*. Two systems concerned by the monitoring in this thesis which are the core and the *HE* of the *NRR*. We described the different experiment methods used to measure some parameters in the core such as the *Pn*, the ρ and the *Tf*. Then, we detailed the more used analytical approaches used to compute the *HE* parameters particularly, temperatures and *FR*s. We not that these parameters will be estimated in the next chapter. Therefore, this chapter is considered as a theoretical support for *Chapter V*.

For the analytical method used for the estimation of the *HE* parameters, we can conclude that *ε-NTU* and *KF* can be used even some parameters measurement of a *HE* are not entirely available. By using the *LMTD,* we obtained a result better than that obtained by the *HB* and *ε-NTU* methods, but the *methods combination* approach seems better. By using the *KF*, we have obtained good *outlet temperature estimation* with a *MAE* less than one *milli* °*C*. As mentioned *previously*, the *LMTD method* is used as the *KF* to estimate the *exit temperatures* of both fluids of the *HE*. Despite its accuracy is less than obtained with the *KF*, it can be used for *accommodation* which the *KF* cannot do. In spite of its quality, the *KF* predict only the outlet temperatures. Consequently, the other methods, *i.e.,* the *HB* and the ε-*NTU* and the *methods combination* are still needed for the estimation of the *inlet temperatures* and *MFRs* of the *HE*. When all *temperatures measurements* and *MFRs* at both streams of a *HE* are available, as in our case, all cited estimation methods can be applied. As sometimes, not all of these measurements are available, and a more realistic situation is the case where only the *inlet temperatures* and *MFRs* are measured. In this case, only the *KF* can be applied for *FDe*.

Finally, the obtained results of the *FS* of the temperatures and *MFR*s of the *HE*, by using the *mathematical estimators*, *CM* and *KF* are much *satisfactory* for this kind equipment. in addition to the temperatures and *MFR*s, we note that we can also supervise the *pressure* of both streams of the *HE* which is proportional to the *FR*. However, as this work used much more the data-based calibration, it is important to repeat this calibration periodically because some *HE* coefficients change with time, especially ε_n which is sensitive to the *fouling*.

CHAPTER II

Fault Supervision

In the literature associated to the supervision domain, we can find several, sometimes, divergent definitions. By a concern of clarity, this chapter suggests first of all describing the fundamental terminology of the supervision which is useful for the understanding of detection, diagnosis and control of faults at plants. Therefore, this chapter is an introductory aiming at recalling, initially, the terminology used for the supervision of fault, encountered in the literature and retained in this thesis, far from ambiguities and overlaps.

The task of responding to a fault involves timely detection, isolating the causal origin, locating the position, identifying the types of the fault and finally taking the necessary steps to bring the process back to within the normal operating limits. It sets up the concepts of monitoring (detection and diagnosis) and correction.

II.1 - Introduction

Variety and sometimes divergent definitions mentioned in various works makes that we consider important, for a better understanding, to establish a terminology on the most terms used in this thesis. These definitions were extracted from variety of references, among them; *(Lefebvre, 2000; Isermann, 2011; Miljković, 2011, Olivier-Maget, 2007).* Hence, one can find in literature definitions which are completely different from those that we propose.

One of the major challenges in instrumentation is to *detect, diagnose* and *correct erroneous measurement data*, which is essential to a robust and efficient *operations* of the *plant systems*. Therefore, it is necessary to regularly ensure correct operation of these devices by continuously monitoring their faults particularly, those having great importance for safety. The role of *supervision* is to *monitor degradations* and *changes* in systems during their *normal operation* and to control the *faults* as early as possible before they lead to *failures* by taking proper decision and undertaking specific actions for *accommodation* and *reconfiguration* to insure optimal and sure management of operating modes of a process, and to keep the system working and avoid damage of the process. The modes and states are defined from the data analysis, system knowledge and the know-how of operators. Therefore, most all the available information on the system are needed to be able to detect eventual process dysfunctions, diagnose them and react in consequence in manner to insure a regular operation even in abnormal situations.

The supervision consists mainly to *feel*, *analyze* and *act*. Otherwise, in supervision system, association of two major functions must be taken into account; *FM* and *Fault Control (FC) (i.e., accommodation, reconfiguration, reconstruction, reconciliation, etc.)* to recover from the fault *(Zemouri, 2003; Olivier-Maget, 2007; Allahham, 2008; Samantaray, Ghoshal, 2008).* The monitoring consists of *detection* which determines whether the process is in normal operation or not by indicating the presence of faults, and *diagnosis* executed after detection of abnormal process state which gives information about the declared faults by processing on-line available data. *FC* is performed in situations where parameters or constraint structures change due to a fault.

Supervision systems include a set of tools and techniques for the *FM* and *control* of industrial processes in normal working conditions as well as in the presence of *failures (Maciejowski, 2002).* So, Supervision covers normal and abnormal operation aspects of a system. In normal operation, its role is to monitor and control the execution of the operation and in the presence of a fault, the supervisor must take all the correct necessary decisions to ensure the return to normal operation. Therefore, supervision has a *Decision-Making (DM)* and operational role in order to resume the order. The general architecture of the *supervision* is presented on *Figure II.1* and then illustrated on *Figure II.5.*

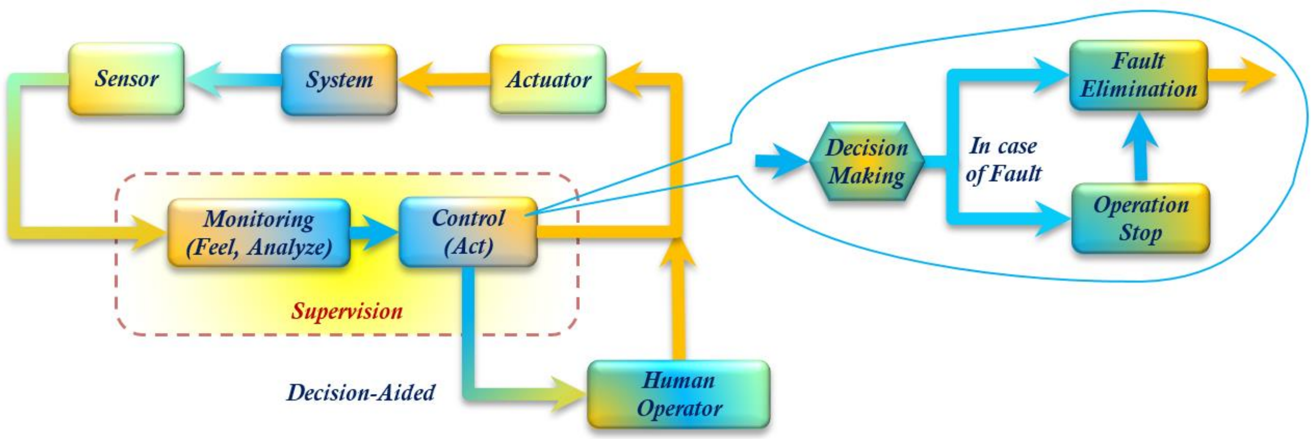


Figure II.1 - General architecture of on-line FS system.

Nevertheless, in some cases, supervision is not any more a simple channel of monitoring functions (*detection - diagnosis*) and *reconfiguration*. Monitoring models much more complex can be set up according to the considered process, the type of faults and also the production.

II.2 - Faults and Operating Modes

Modern automated industrial processes are vulnerable to faults. Indeed, faults in actuators, sensors, process equipment or within the controller are inevitable and unpredictable. These faults can be amplified by the closed-loop control systems, and faults can develop into malfunction of the loop. The closed-loop control action may hide a fault from being observed. A situation is reached in which a fault eventually develops into a state where loop-failure is inevitable. The fault consequences can lead to serious degradation in the system performance and may even lead to a complete breakdown of process operation at a plant level, if not handled properly in the control system design.

Various faults can occur in different stages of an industrial system and particularly *NPs* such as the *instrumentation (e.g., sensors* and *their acquisition channels*, *radiation detectors* and *their detection channels, actuators like valves* and *their command system), equipment (e.g., water pumps, HE), processes*, and *structures*. These faults can be *stuck valves*, *process fouling*, *broken pipes*, *sensor drift*, *damaged motor bearings*, *etc., (Venkatasubramanian et al., 2003b; Kidam et al., 2010).* Faults can have a significant impact on system safety and performance for *NPP*. For example, drift in *steam generator feed water flow* sensors can result in reactor power output reduction by as much as 3% *(Chan, Ahluwalia, 1992).* A stuck open relief valve created a loss of coolant scenario in the *Three Mile Island* accident, which was a major reason for the disastrous outcome *(Broughton et al., 1989).*

Fault is considered as any sort of unexpected and unpermitted *anomaly* such as *change*, *degradation* or *deviation* of at least one characteristic property (feature) of the system from *normal (i.e., acceptable, usual, standard) condition and* operating behavior and performance in the process (the cooling system and core of the *NR* in our case), caused by malfunctions of components and if unchecked can induce an intolerable *failure* (*Breakdown*) in the system behavior and may further deteriorate the system's performance as is shown on *Figure II.2 (Olivier-Maget, 2007; Abdul Rahman, 2010; Hwang et al., 2010*; *Ma, 2015).* We can find in the literature some technical words which have closer meaning or are in confusing with the *fault* word, such as *anomaly*, *damage*, *default*, *error*, *malfunction*, *symptom*, *uncertainty* and *so on (Zemouri, 2003; Worden, Dulieu-Barton, 2004; Olivier-Maget, 2007).*

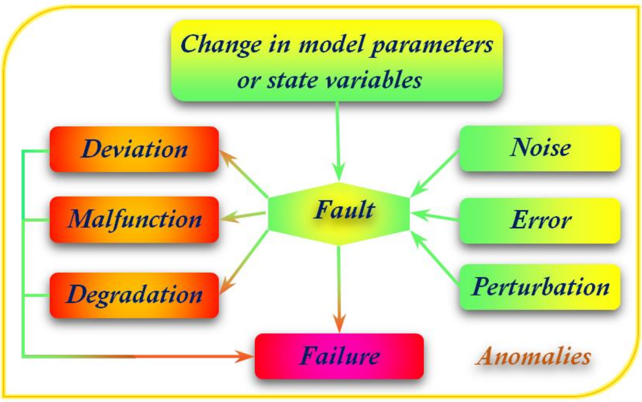


Figure II.2 - Various sorts of anomalies (Venkatasubramanian et al., 2003a).

While a fault is considered non-normal behavior in contrast, failure or break-down can be defined as a permanent interruption of a systems ability to perform a required function under specified operating conditions

(Isermann, Ballé, 1997) (Figure II.3). Usually, a fault is minor when compared to a failure, but most failures tend to stem from ignored or undetected faults *(Zhang, 2009; Ma, 2015).*
For simplicity, the term *fault* is used to refer to both *faults* and *failures* herein.

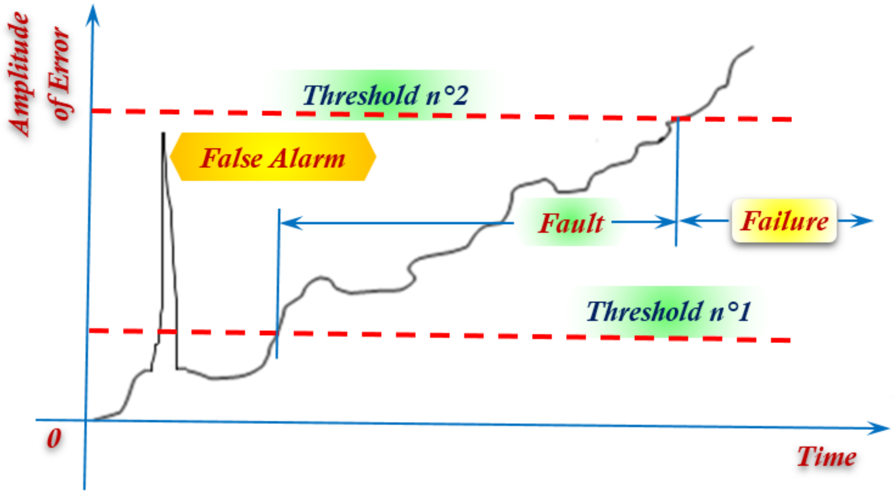


Figure II.3 - Relation fault – failure.

Faults can appear in systems as a *single fault* or *multiple faults*. They provoke the *degradation* of their performance, accuracy and efficiency. Fault does not represent stop of operating altogether because this means failure (100% *degradation*) *(Himmelblau, Bhalodia, 1995).* But, unless corrected, fault can progress to be a *failure (Isermann, Ballé, 1997; Venkatasubramanian et al., 2003a).* The degradation of the equipment is characterized by all the period when the characteristic amplitude of the parameter remains under the threshold of alarm. The detection of crossing of this threshold provokes a generation of synonymic alarm of a failing event. The equipment is then in a situation of breakdown. The *fault effects*, also called *fault indicators* or *fault signatures*, allow decision on the occurrence of a fault and its analysis *(Olivier-Maget, 2007).* Therefore, to monitor variety types of faults with adequate tools, it is necessary to model all their signatures that can lead to alarms, what is called fault evaluation *(Tarifa, Scenna, 2000; Jiang, 2011).* At any given time, it is difficult to distinguish between the effect of disturbance, noise and fault because they often manifest themselves in the same way in measurements. Nevertheless, the difference lies in their temporal behaviors. Compared to the noise, a fault acts on the system with a different manner, thing which helps in its detection. All systems components are subject to fault due usually to various intrinsic (*e.g.,* manufacturing inefficiencies, obsolescence), extrinsic reasons (*e.g.,* mishandling); incorrect calibration; interactions with the environment (*e.g., severe shocks*, *vibration*, *heat*, *friction*, *dust*); and other causes of performance degradations *(International Atomic Energy Agency, Vienna, 2008; Balaban et al., 2009).*

Anomalies can be classified according to the degree of criticality: *fault* (*assimilable*) when it has no impact on the performances of the device features; characteristic when it can be by-passed by a *corrective action*; and *failure* (*critical*), when it requires an emergency action (*repair* or *substitution*) *(Olivier-Maget, 2007).* There are *different ways* to *classify faults* according to *various standards (Zhang, 2009). First*, faults can be characterized by their *temporal features*. As shown on *Figure II.4*, the speed and shape behavior of fault appearance can be very different, from *abrupt* (*sudden* or *coarse*) change in time to very slowly developing (*incipient*, *progressive*, *drifting* or *subtle*) passing by *intermittent* (*discontinue*) *(Fragkoulis, 2008; Balaban et al., 2009; Jiang, 2011).* (*a*) *Abrupt faults* are dramatic and persistent in which the magnitude is scaled by a factor α where the form of the waveform itself does not change. They are usually accompanying by significant deviations from steady state operations. *Abrupt* fault can be a failure and consequently have to be detected early enough to avoid bad consequences *(Malhotra,* Huang, 2002; Fragkoulis, 2008; Zhang, 2009). (*b*) *Incipient fault* sometimes called also *soft faults* (Chen, Patton, 1999) has a slow temporal behavior (*minutes* to *hours*). It develops gradually from nothing (no fault) to a larger fault. It includes *bias*, *scaling*, *gain, offset* and *drift* (Zhang, 2009). This type of fault is characteristic of a fouling in the *HE*s and is very common in analog instrument due to incorrect calibration, internal temperature or physical (material) changes. In some sense, this fault is the opposite of *abrupt* changes however, *incipient faults* have a weak effect and almost unnoticeable when it occurs. Although it may be tolerable in its early stage however, it may develop to cause very serious consequences (Fragkoulis, 2008; Zhang, 2009). Therefore, the monitoring of *incipient fault* can be considered as the hardest challenge task in a safety-critical environment (Chen, Patton, 1999). (*c*) *Intermittent fault* is a consecutive of arbitrary amplitude pulses appears and disappears randomly for very short periods of time (order of *seconds*). It can be considered as a particular case of *abrupt* fault with the particular property that the signal returns in an unpredictable way in its normal value. Such failure can appear in any of the two failure modes described above. These faults can be provided by bad contact in slots and cables connection and in dry welds for electronic components. They appear also in sensors like thermocouples due to corrosion or breakage of junction and in proportional counter when the central electrode is bad welded. Thus, due to the random nature of the intermittent fault, they are most difficult to monitor. Sometimes *intermittent faults* can have disastrous consequences.

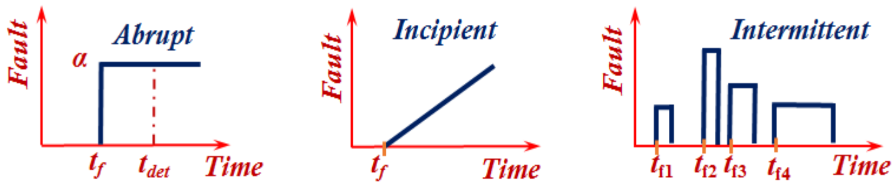


Figure II.4 - Common classification of faults according to their time-variant behavior, where t_f and t_{def} are respectively the occurrence time and the detection time of fault.

A *second classification* most often used in the process industry based on the *origin of the fault* (Zhang, 2009). (*a*) *Equipment malfunctions*. In many cases, errors occur in actuators or sensors. A faulty actuator is not able to operate accurately and promptly to provide proper input to the process. With the devolvement of process dynamics, this local malfunction may lead to deterioration of the entire plant. If the failed sensor happens to be a part of a feedback control loop, the malfunction is rapidly propagated through the causal channel of the loop. (*b*) *Structural process changes*. Despite its infrequency, this type of fault tends to result in catastrophic consequences if no effective response action is promptly taken. The challenge of a structural fault is the lack of an accurate mathematical description. (*c*) *Parameter changes*. Such changes arise when a disturbance enters the process through one or more exogenous inputs. It should be noted that the more common faults in the process industry are *parameter changes* and *equipment faults*.

The faults can be also classified according to the manner how they act on the system. Faults may be represented as unknown extra inputs acting on the system which dependent on *measurement* and *process* and are function of the *inputs* and *states*. In this case, faults are considered *additive.* Faults may be also represented as changes of some system parameters which dependent on the process and fault dynamics, considered as *multiplicative* called also *non-additive* (Gertler, 1998; Balaban et al., 2009; Hwang et al., 2010). All these two types of faults and noise act together or individually on different parts of the system as shown on *Figure II.5* (Venkatasubramanian et al., 2003a; Zhang, 2009; Hwang et al., 2010).

Any fault can be classified as minor faults and major faults depending on whether or not there is a need of reconfiguring the controller in the closed-loop. The faults can be also considered as *intermittent* and *permanent faults* (Allahham, 2008).

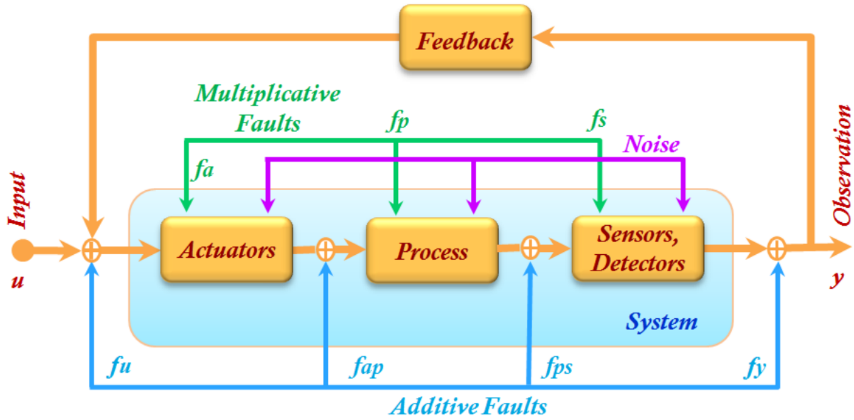


Figure II.5 - Source and type of faults in a control system, where f_i represents a fault with the subscript i can be u, y, a, p, s, ap or ps which mean, respectively: input, output, actuator, process, sensor, actuator-process and process-sensor (Mouzakitis, 2013).

The presence of faults in a system induces effects and consequences on its operation behavior dependently of the nature and severity of these faults. Therefore, a system presents usually several operating modes *(Zemouri, 2003)* as is illustrated by *Figure II.6*. (*a*) *Nominal operation mode* of equipment or the industrial system corresponds to the state when it performs its mission in the operation conditions required by the constructor and with requirements expected from the user. (*b*) *Degraded operation mode* corresponds to the partial fulfillment of the system mission with low performance. In this case, there is degradation in the system behavior but no yet stop of operation.

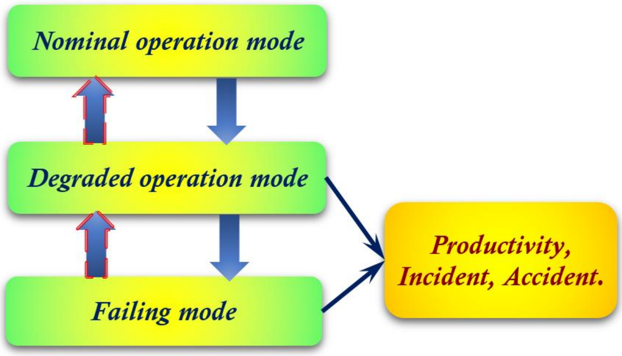


Figure II.6 - System operation modes.

(*c*) *Failing mode* corresponds to bad operation of the system, developed after an abrupt fault or from an evolution of degradation such as intermittent and incipient faults. This mode is characterized by causes responsible of its appearance; in this case we speak about *Cause-Effect (CE)* problem. Since this link is not unique (*i.e.*, an effect can have multivariate causes), therefore every equipment or system can possess a single nominal mode but several failing modes.

II.3 - Fault monitoring

Indeed, the *detection* of a malfunction helps to avoid any degradation that may affect the system to be monitored and the elements of the neighboring environment (users and equipment). This brings us to a more general notion called "*monitoring*", considered as essential discipline in the field of reliability.

Monitoring has become an active research area for dynamic systems since 1970's. In the beginning, it is restricted to industrial applications at high level of risk such as the nuclear, chemical plants and aeronautic *(Daly et al., 1979; Desai et al., 1979)*, as well to point activities such as the armament industry and aerospace *(Deyst* *et al., 1977)*. In the last decades, it has received more and more importance principally due to an increasing need for higher performance, safety and reliability.

The first major survey was written by *(Willsky, 1976; Mironovskii, 1980; Isermann, 1984).* Earlier significant books were published on this subject *(Himmelblau, 1978; Pau, 1981; Basseville, Benveniste, 1986).* They are followed by summary especially in synthesis papers *(Milne, 1987a; Isermann, Ballé, 1997),* as well in synthesis books such as *(Brunet, 1990; Zwingelstein, 1995).*

The *detection* and *diagnosis* of malfunctions in technical systems include *production equipment*, *transportation vehicles*, and *household appliances*. While the need to detect and diagnose malfunctions is as old as the construction of such systems, advanced *FDe* has been made possible only by the proliferation of the computer.

In *NP*s, the parameters to monitor are: *nuclear parameters* such *power, neutron life cycle*, ρ and ρ *coefficients,* and *neutron poisons; thermal-hydraulic parameters* such as *Tf, pool temperature, inlet* and *outlet temperature, pressure* and *flow* of the *thermal loops;* and *control parameters* such as *control rods position (Mesquita, Souza, 2010; Gang et al., 2013). (Clayton, Poore, 2014)* Gave a list of monitored parameters of various systems in *Boiling Water Reactors (BWRs). (Hofstotter et al., 1999; Makai, Végh, 2017)* gave a list of monitored parameters of the core in *BWRs,* and *Pressurized Water Reactors (PWRs).*

Monitoring consists notably to detect faults by observing the system evolution, then diagnosing them by localizing the faulty elements and identifying the primary causes *(Olivier-Maget, 2007).* A *monitoring system* must be able to *realize* and *analyze* the state of a process at any time, given a stream of observations *(Casimir, 2003),* and to *extract* necessary information allowing to discover the failings of systems and to diagnose them *(Zemouri, 2003; Olivier-Maget, 2007; Allahham, 2008)*

Monitoring has a passive role; its tasks are limited for providing information on the state and has no direct action on the system or its control. Therefore, *monitoring* is *informative* tool, which consists, essentially in recognizing the operating mode of system during the regular operation by *analyzing* its state and *providing* indicators through observations based on the real-time process of data and signals *(Zemouri, 2003; Kempowsky, 2004; Allahham, 2008).*

The objective of the plant *monitoring* system in any potentially unsafe scenario is to give the *plant operators*, in case of *fault*, appropriate inputs to *formulate*, *initiate* and *perform* the *corrective actions.* Therefore, the *FDD* system gives the necessary help to significantly reduce risks associated with the faults appearance and to prevent bad on global operations.

Hence, the *FM* structure Basically, consists of two main successive functions: the *FDe* and the *FDi (Zemouri, 2003; Tidriri et al., 2016), as is presented by Figure II.7 (Racoceanu, 2003; Palluat, 2006). First, FM* consists *to learn* on data acquired by the components and instrument (*e.g., sensor*) of the system to be monitored; *to feel* and so *detect* undesirable process changes and anomalies against the normal operation which means that the system is in abnormal operation. A detected fault is then expressed by the generation of symptoms giving more or less elaborated information about the faults *(Gertler, 1988; Frank, 1990). Second,* after a fault has been detected, the *FDi* will take place*(Ma, Jiang, 2011; Khentout et al., 2018).* It *analyze* the fault information and give necessary explanations to establish a tools for its *diagnosis (Palluat, 2006).* The set of information and analysis of faults are provided to the operators in the control room. However, in some references the *FDe* is considered as part of *FDi Frank, 1996; Isermann, 1997; Frank et al., 2000a; Bentoumi, 2004; Poongodai, Bhuvaneswari, 2013; Capacho et al., 2014; Gao, 2015a; Gao, 2015b; Świercz, 2015; Tidriri et al., 2016; Vogl, 2016; Huh et al., 2019; Skliros et al., 2019).*

The *FDI* consists to *locate*, *identify, isolate,* and pinpoints exactly their causes (origin of fault) *(Mosallaei et al., 2007).* Hence, the monitoring is often called *FDD (Olivier-Maget, 2007; Ma, Jiang, 2011; Ma, 2015).* In most cases, the *FM* is limited to the *FDe* and the *FDi* is omitted particularly, when the system to be monitored is too complex. So, the *FDe* is *indispensable* task but the *FDi* is usually *required*.

The output of the *monitoring* system may be *simply* an alarm signal that takes two values, high when fault is detected and low for *fault-free*. In sophisticated case, this output provides a knowledge on faults such as their *location*, *amplitude, causes*.

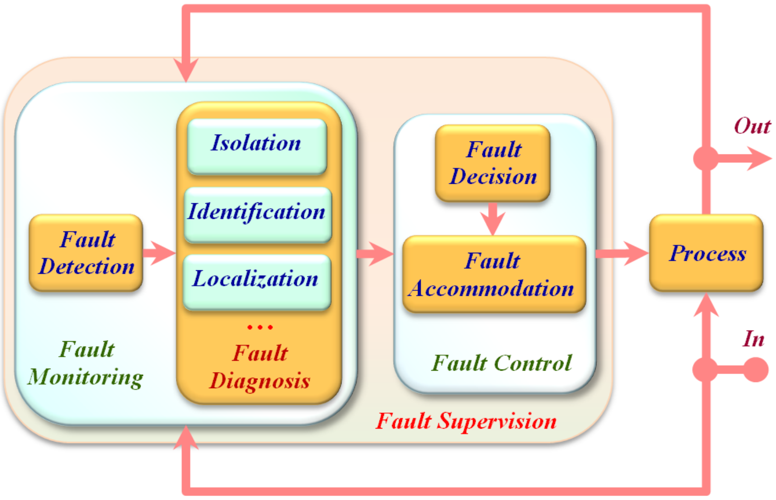


Figure II.7 - Bloc diagram of the FS applied to a process.

Particularly, when the model is used, the *FM* is usually performed in *two consecutive steps*: the *generation* and *evaluation* of *residuals (Ben Rahmoune et al., 2017).* In this case, the *FM* is limited to the composition of *Detection* and *Isolation/Identification*; and it is called *FDI (Zhang, 2009; Hwang et al., 2010; Samy et al., 2011).*

So, the *FDI* combines in the same time the *detecting* of *abnormal change* or *deviation* in the behavior or in the state of a system which gives place to the generation of *faults* in the form a symptom; and *isolating* these faults which means finding the root causes of the faults which leads to the location of the elements responsible of these faults *(Mamar, 2008).*

Beside the *FM*, *FDD* and *FDI*, various technical terms have evolved and used in the literature to describe the process health and its data checking by using different techniques which may be referred to such *surveillance (Keyvan, Rabelo, 1992); Sensor Validation (SeV) (Worden, Dulieu-Barton, 2004; Kasinathan et al., 2009; Ma, 2015)* prognosis; *FTC*; *Failure Detection, Isolation/Identification and Accommodation* (*FDIA*) *(Jiang, 2011; Samy et al., 2011) or Reconfiguration* (*FDIR*) *(Hwang et al., 2010); condition-based calibration*, *preventive maintenance*; *Condition-Based Maintenance* (*CBM*). Other terminologies are used in conjunction with the term *monitoring* to specify certain monitoring tasks and particularities such as *conditions monitoring* and *health* (*performance*) *monitoring (Fantoni et al., 2003; Ma, Jiang, 2011).* More common terminology for the *FM* and for the *FS* are suggested in *(Zemouri, 2003; Worden, Dulieu-Barton, 2004).*

Some references use the terminology *FDD (Venkatasubramanian et al., 2003a; Mosallaei et al., 2007; Ma, Jiang, 2011)* instead *monitoring* to avoid any ambiguity between monitoring and *FDi*. This ambiguity is resolved when the *FDi* is specified such as in *Fault Detection and Isolation (FDIso) (Samy et al., 2011; Adouni, 2013; Anzurez-Marin, 2014), Fault Detection and Identification (FDId) (Kullaa, 2013) and Location* (*FDLo*) *(Fragkoulis, 2008; Reyes-Archundia, 2015), Fault Detection, Identification and Isolation (FDIdIso) (Dorr et al., 1997),* an abbreviation used by many publications and books. We note that *FDI* in literature means *FDId*, *FDIso* or both, terminology adopted in this thesis.

The *FM* can be performed with two main manners: on-line and off-line. Some terminologies are used in conjunction with the term *on-line* such as *Real-Time Monitoring* (*RTM*), *On-Line Monitoring* (*OLM*) and *On-Line Calibration Monitoring (OLCM) (Fantoni et al., 2003; Ma, Jiang, 2011).* As *off-line monitoring* is temporarily and simple, a *continuous on-line* or *real time process monitoring* can be also easily applied if an *early detection* can be achieved *inexpensively* and *timely*. The *on-line* or *real-time FDe* and *FDi* means that the equipment is constantly monitored during its regular operation by a permanently connected computer, and any discrepancy is signaled almost immediately. Monitor a system continuously during operation, is often referred to as *OLM*. A number of different *OLM* implementations have been developed over the past years and some plants already use it in addition to the time-based calibration program to obtain additional information for plant maintenance. A continuous real-time task of determining the conditions of a physical system, by in recording information, recognizing and indication anomalies in the behavior *(Simani et al., 2003; Ma, Jiang, 2011).*

The successful implementation of *OLM* can provide a means to detect quickly small deviations, enough to facilitate timely action. It is very important the early *detection* of any component malfunction before it can lead to more substantial equipment *failure* which prevents damage or downtime to the system. Therefore, *OLM* can provide, over time, an information and assessment of instrument and equipment performance and provide a basis for determining when adjustments are necessary. Elimination or reduction of unnecessary adjustments and calibrations can reduce associated labor costs, personnel radiation exposure and the potential for miss-calibration. More Benefits of *OLM* is given in *(Hofstotter et al., 1999).*

The *preventive*, *predictive* or *dynamic monitoring* (*Figure II.8*) consists to analyze the present and past state of the physical system to forecast the future system degradations, faults and failures, and determine their consequences on the future system operation *(Kempowsky, 2004; Olivier-Maget, 2007).* The *preventive monitoring* is composed of the *preventive detection* and of the *preventive diagnosis* also called *prognostic (Zemouri, 2003; Mahdaoui et al., 2009).* Install a *preventive monitoring system* consist so in being able to detect the degradation before the failure event pairs.

A *survey* of *data-driven prognostics methods* can be found in *(Schwabacher, 2005).*

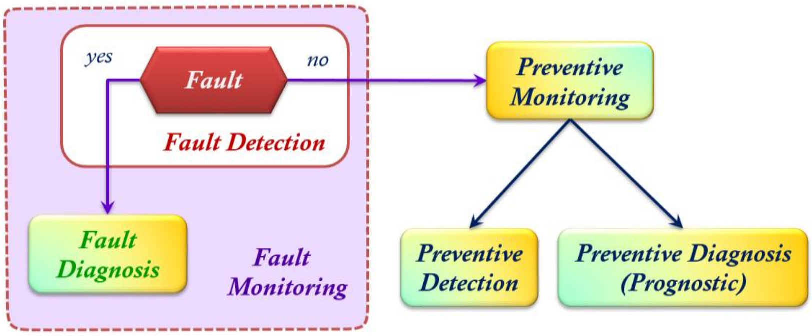


Figure II.8 - Classical and preventive monitoring.

Preventive detection of fault consists to foretell a future degradations faults and failures. *FDe* is different from *fault prediction*. The first deals with the faults that had happened and its result are *certain*; but fault prediction deals with the faults that will happen, so its result is *random.* Therefore, it needs probability to describe the result of fault prediction *(Olivier-Maget, 2007; Zhang, 2010).*

A *preventive diagnostic*, *prognostic* or *prognosis* is an engineering discipline focused on predicting the time at which a system or a component will no longer perform its intended function. *Prognostic* is different from *diagnosis*; *diagnosis* is done only when a fault has occurred whereas, prognosis deals with assessing the health of the equipment and predicting the remaining useful life time *(Manoharal., 2017).* Prognostics include detecting the precursors of a failure, identifying the causes and to locate organs which entailed a particular degradation, and predicting how much time remains before a likely failure. Furthermore, the *prognostic* or function allows the determination of the consequences of a failure on the future operation of the system. Two kinds of prognosis can be distinguished; *preliminary prognosis* and *preventive prognosis*. The *preliminary prognosis* looks for the inevitable consequences of a failure (identification of all the tasks that can no longer be performed by respecting the scheduling). In this case, only the failures and their causes are known. The *preventive prognosis*, focuses on the latent error and the propagation of failure (the repetition of the same failure). In this case, only failures whose effects are not immediately detected are considered in this case. The preventive prognosis determines whether there are other products that are affected by the same defect that would induce the same symptom in the future. This type of prognosis is used to prevent the execution of activities leading to the detection of the same symptom. Prognostic is the most difficult task compared to *FDe* and *FDi* *(Boufaied, 2003; Fantoni et al., 2003; Poongodai, Bhuvaneswari, 2013).*

The capability to monitor faults, in *instrument*, *equipment* and *systems*, depends on the availability of suitable *measurements*. *FM* treats at the same time *digital data* (*e.g.,* from sensors) and *symbolic data* (*e.g., knowledge* on the considered system). *(Dubuisson, 1990)* has considered these two types of data as necessary for the *monitoring* operation. These data can be *global* and can be qualified as *off-line* or *a priori* on the system such as the knowledge based on the past of the system; *instantaneous* corresponding to a set of the elements we have at a given moment to make a decision and to exploit it. But these data, especially *digital*, are usually associated with errors and noise and if they are not properly handled, they may lead to erroneous estimation of equipment performance. Sometimes due to the difficulty to access to the data, simulated results can be used instead *(Racoceanu, 2003; Fragkoulis, 2008).*

II.3.1 - Fault Detection

The detection is a crucial phase for monitoring because it presents the decision stage which allows launching *FDi* with the most complete manner possible. Indeed, it allows to administer and to analyze an important mass of available information. Certainly, it is easy from fault to find the effects, but the reverse "to find fault from effects" is not always feasible.

The purpose of *FDe* *(Allahham, 2008)* is to *unregister* the *time* of *apparition* (*Figure II.9*) *(Mohammadi et al., 2010)* of *any small abnormal changes* and *anomalies* *(Proceedings of the 6th International FLINS Conference, 2004)* in the behavior or state of a system or process and *generate* an alert such as luminous or sound *alarm* *(Xin et al., 2015)* to the *supervision operators* to the presence of a fault for intervention *(Allahham, 2008)* early than a conventional system *(Rahman, 2009; Allahham, 2008), before* they *evolve* (*leads*) into *failures* *(Mohammadi et al., 2010).* Detection consists to compare the current behavior to the reference one. So, it detects any deviation from normal system behavior and generates a symptom (*Figure II.9*) then then makes a decision as a result of the comparison. Therefore, *detection* allows to take into account abnormal situations due to real failures on the process but, also, unexpected situations which correspond to a normal operation of the process and which have not been considered during the development of the model of behavior.

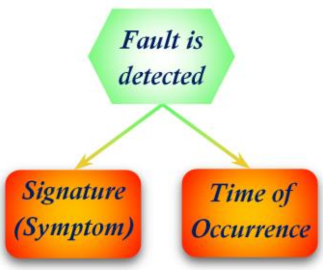


Figure II.9 - Constituents of FD.

FDe usually involves making a binary decision - either that something has gone wrong or that everything is within normal operating limits. So, this function makes it possible to characterize normal or abnormal operation of system.
Basseville and *co-workers* started work on monitoring plant parametric changes *(Basseville, Nikiforov, 1993; Benveniste et al., 1987)* from which they developed a procedure for the detection and isolation of *abrupt change* in the parameters of a process multiplicative or *non-additive faults*. More details on *FDe* is given in many *papers (Palma et al., 2002; Kempowsky, 2004; Li, 2003; Evsukoff, Gentil, 2005; Nabeshima, 2005; Allahham, 2008; Mamar, 2008; Rahman, 2009; Mohammadi et al., 2010; Jiang, 2011; Gertler, 1998; Yoo et al., 2006),* books *(Korbicz, Koscielny, 2010)* and *thesis (Bentoumi, 2004; Olivier-Maget, 2007; Allahham, 2008; Fragkoulis, 2008; Letellier, 2012).*

Fault detectability is a property of the system under consideration describes how a *fault* affects the system behavior and how a *cause* changes in the system output. It should be expressed independent of the system input variables, disturbances as well as model uncertainties. Finally, the *structural fault detectability* should be independent of the type and size of the fault under consideration *(Ding, 2008; Hwang et al., 2010).* It is usually understood that the *small amplitude, abrupt (Malhotra, Huang, 2002)* and *slowly drifting bias faults* (*incipient faults*) are difficult to detect *(Napolitano et al., 2000; Campa et al., 2002b).* Therefore, the *capabilities* to *detect* these types of changes are strictly related to three levels of noise in the measured signal; accuracy of the used approach; and on-line learning rate *(Campa et al., 2002b).*

The *Mean Detection Time (MDT)* number of *Undetected Faults (UDs),* and the percentage of *time* that the *residual* remains *above* the set *threshold* prior to a fault being introduced are indicators of the *FDe* during the test procedure which characterizes the *FAl*. *FM* can never be performed with absolute certainty, because of circumstances such as *noise*, *disturbances*, and *model errors*. Moreover, there is always a *trade-off* between *FAls* and *missed detections*, the proper balance depending on the particular application *(Samy et al., 2008). FDe* is also characterized by other parameters such as *minimum detectable fault*, *detection ratio; number of FAls* and *FDe delay (Campa et al., 2002b).* The *FDe delay* is the difference between the instant of appearance of a fault and the time of its detection *(Brijeshkumar et al., 2013).*

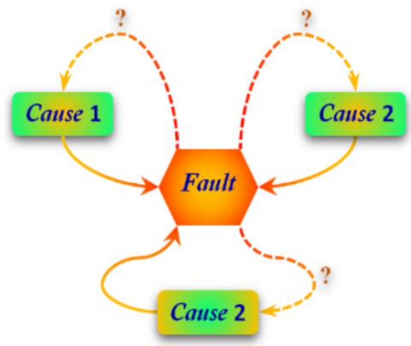
The execution of the *FDe* procedure passes throw *two phases*: building the *FDe* function and formulating the mathematical functions as model, are done in the *off-line phase*, while receiving data stream from the monitored system, and applying the *FDe* function on the incoming data stream are done in the *on-line phase*.
One of the most important properties of detection is to be sufficiently sensitive to detect faults at any time, and robust to avoid *FAl*s in presence of noise and disturbances. Thus, *robust detection* is a desirable feature in the design of an effective *FDe* algorithm.

II.3.2 - Fault Diagnosis

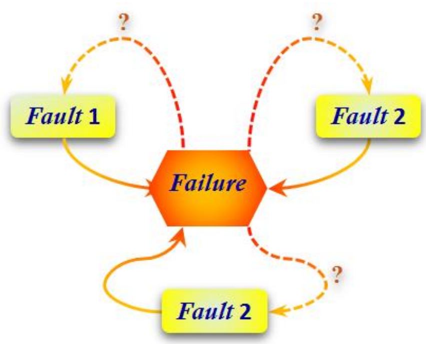
Indeed, *diagnosis* is etymologically coming from the *Greek* and means "*dia*": *by*, "*Gnosis*": *knowledge*. When a fault is *occurred*, it is not sufficient to detect it and to know its symptom, but it is also necessary to describe and analyze the nature if the symptom and to obtain *information* about it, which is the task of the *FDi* step *(Anzurez-Marin, 2014).*

FDi, also called *Fault Analysis (FAn) (Patel, Patel, 2015; Ghazali, Ibrahim, 2016)* consists to evaluate and interpret correctly the *symptoms* revealed during the detection phase resulting from a degradation of one or several components in the physical system *(Olivier-Maget, 2007),* in order to *locate* the *position of* faulty components, *identify* their *type* (*nature*), *size* (*amplitude*) and *origin* by *determination* of the *causes;* and give the necessary *explanations* and *details* on these *faults (Allahham, 2008; Fragkoulis, 2008; Rahman, 2009).*

Therefore, the purpose of the *FDi* is mainly to determine: (*a*) *Type* allows giving the type of the detected fault such as the *magnitude*, *size*, *shape* and *nature*. (*b*) *Position:* allows determining exhaustively the organs, element or components of a physical system that is faulty and led to a particular observation and exact the area or position where the fault is happened *(Olivier-Maget, 2007; Mamar, 2008; Ben Rahmoune et al., 2017).* (*c*) *Cause* that led to an abnormal situation. From the observation of a fault state, the *FDi* function *determines* and *finds* in physical systems, chemical and nuclear process plants *(Becraft, Lee, 1993)* the *root causes* or *origins (Yoo et al., 2006),* such as *software;* and *physical component, equipment and sub-system* which engendered *anomaly* (*e.g., degradation, faults, failures)* and led to an abnormal situation *(Orantes Molina, 2005, Fragkoulis, 2008; Zhang, 2009).* These causes can be internal or external to the equipment *(Zemouri, 2003).* Indeed, for a given cause, it is easy to predict its resulting fault. Also, for a given fault, it is easy to predict its effect and resulting failure. But identifying the cause from the fault or the fault from the effect is a difficult task, because a fault and failure can usually be explained by several cause and faults respectively (*Figure II.10*).



Causes 1, 2 and 3 lead to the same fault but, the reverse operation is complicated?



Fault 1, 2 and 3 lead to the same failure but, the reverse operation is complicated?

Figure II.10 - Fault - causes and fault – failure relationship (Olivier-Maget, 2007).

It is then a question of comparing the observations to provide the correct explanation. Some methods can be used to find fault causes and origins such as the *knowledge-based reasoning*, *cluster analysis*, *PR* and *signature analysis, qualitative reasoning, statistical analysis*, or any number of *parametric* and *nonparametric models (Venkatasubramanian et al., 2003c).* In this context *abductive diagnosis* concept is emerged from the definition proposed in *(Peng, Reggia, 1990).* In this type of logical reasoning, an inference is involved that goes up from effects to causes by modeling and finding satisfactory explanations and analyses of the relations *CE (Ayoubi, Isermann, 1997)* associating the *initial causes* (*e.g.,* failures of components) with the observable manifestations as *consequences* (*i.e.*, the symptoms) *(Hamidoud, 2007; Allahham, 2008).* Therefore, the *FDi* can be considered as function which establish a link from *causes* to *effects* between the observed symptoms and the occurred faults *(Becraft, Lee, 1993).* It consists to analyze the symptoms to deduct the *internal causes* being a part of the monitored system or *external* to this system paralleling the field of medical *diagnosis*. It based on that other faults cannot produce the observed behavior *(Heredia et al, 2008; Letellier, 2012).*

All the *FDi* tasks (*i.e.,* the determination of the *type*, *position and causes* of *fault*) are generated as *FDi data* and sent to the operators at the control room for efficient and accurate *decision* on technical processes at various levels. The monitoring system must be able to decide when process is in a normal situation of operation, and when a corrective action must be applied. In *DM*, this corrective action corresponds to the *reconfiguration* step of the command in order to return process in a normal operation mode. Therefore, *FDi* is considered more complicated compared to *FDe*.

In the most cases, the *FDi* function is composed mainly of four functions (*Figure II.11*) : the *isolation (Evsukoff, Gentil, 2005; Hwang et al., 2010); identification (Desai et al., 1979; Mehranbod et al., 2005); analysis (Frank,* *1996; Frank et al., 2000a; Palma et al., 2002; Yang et al., 2010a; Capacho et al., 2014)* and *localisation (Worden, Dulieu-Barton, 2004; Fragkoulis, 2008), localization (Khaled et al., 2010)* or *location (Burnett et al., 1996). (Gao et al., 2007; Liu et al., 2015)* introduced additional term: *Fault Estimation* (*FEst*) as part of *FDi*. The *FEst* in *(Yoo et al., 2006; Zhang et al., 2009)* means the magnitude or size of the fault.

Figure II.11 - Main FDi constituents and their frequent meanings.

(Allahham, 2008; Zhang, 2009) used the *explanation function* as part of *FDi,* which means a *conclusion* (*i.e.*, formulation and justification). More details on *FDi* and its steps are done in many references *(Grosclaude, 2001; Bouchon-Meunier, Marsala, 2003). (Dubuisson, 2001)* considers the *FDi* problem as a *shape recognition(Olivier-Maget, 2007; Fragkoulis, 2008).*

In some cases, the *FDi* is limited to one or two of these functions. *(Ma, Jiang, 2011; Ma, 2015)* define *FDi* as two basic functions; *Fault Isolation (FIso)* and *Fault Identification (FId);* and *(Zemouri, 2003; Fragkoulis, 2008)* define it as *Flo* and *FId. (Allahham, 2008; Zhang, 2009)* has added the *explanation function* to localization and identification as constituent of the *FDi*. Furthermore, in *(Allahham, 2008; Fragkoulis, 2008),* the detection time (apparition) of fault which is generally associate to the *FDe* function, is associated to *FDi*.

In literature, there is a *conflict* and *ambiguity* between definitions and nomenclature of the main constituents of *FDi*, *i.e., FIso, FId, FLo, FAn,* and some references confuse between them as is shown on *Table II.1*. For example, *(Frank et al., 2000a; Palma et al., 2002; Zhang, 2009)* define *FIso* as *FLo* which locates the possible root causes for the detected fault. *(Fragkoulis, 2008)* define the *localization* as part of *FIso.(Palma et al., 2002)* define *FAn* as *Fid* which is the determination of the magnitude of the fault.

The successful detection of a fault is followed by the *FIso* procedure defined as the ability to distinguish (isolate) a particular fault from others*(Chen, Patton, 1999; Orantes Molina, 2005).*

FId can be defined as the determination of *size* and *evolution (Olivier-Maget, 2007; Fragkoulis, 2008; Ma, Jiang, 2011)* defined *FId* as *size* (*amplitude*) estimation and determination of the probable *evolution* (*time-variant behavior*) of the *fault. (Allahham, 2008)* defined the *FId* as the *apparition time* of the *fault*, its *duration* and its *size*.

There are several issues about *FLo* such as the *fault isolability (Chen, Patton, 1999) efficiency, FIso time* or *fault resolution time* and perhaps of primary importance is the *resolution*. The latest (*i.e., diagnostic resolution*) is defined as the degree of *accuracy* to which faults can be *located*. A test that achieved the maximal *fault resolution* is said a *complete FLo test*. A brief review of the *FLo techniques* can be found in *(Mirzaei, 2009; Gururajapathy et al., 2017).*

The detection function determines the normality or the abnormality of the system in operation. This function often represents a topic of debate concerning its place and we find themselves confronted with the terminology. Many references consider detection as essential information and inseparable from the *FDi*. Therefore, we find in the literature instead of the *FM*, the term *FDi* which includes consequently the *FDe* function *(Gertler, 1991; Reifman, 1997a; Simani, Fantuzzi, 2000; Fragkoulis, 2008).* However, other works consider *FDe* as original part, inextricable and element apart information from *FDi* and view it more as autonomous entity in monitoring such as in the most of references *(Li, 2003; Mamar, 2008, Yu et al., 2014).* This opinion is adopted in this thesis. Some authors avoid this ambiguity in terminology by using the term *FDD (Leger et al., 1998)* or *FDI (Chen, Patton, 1999)* instead *FM*.

<table>
<tr><th>Function/Task</th><th>Which Element</th><th>Type (Nature) : Magnitude or Amplitude, Size</th><th>Cause</th></tr>
<tr><td rowspan="3">Localization, (Localisation, Location)</td><td>Zemouri, 2003; Orantes Molina, 2005; Olivier-Maget, 2007); Ben Rahmoune et al., 2017.</td><td rowspan="3"></td><td rowspan="3">Zhang, 2009; Allahham, 2008; Olivier-Maget, 2007.</td></tr>
<tr><td>Which Element /the Cause</td></tr>
<tr><td>Mamar, 2008.</td></tr>
<tr><td rowspan="6">Identification</td><td rowspan="6"></td><td>Type (Nature)</td><td>Cause</td></tr>
<tr><td>Mamar, 2008; Gertler, 1998; Patton, 1991; Chen, Patton, 1999; Palma et al., 2002.</td><td rowspan="3">Zemouri, 2003; Yoo et al., 2006; Hamidoud, 2007; Allahham, 2008; Bickson et al., 2009;
Zhang, 2009.</td></tr>
<tr><td>Magnitude (Size), Temporal Behavior</td></tr>
<tr><td>Fragkoulis, 2008; Ma, Jiang, 2011;</td></tr>
<tr><td colspan="2">Type (Nature), Cause</td></tr>
<tr><td colspan="2">Frank et al., 2000a; Capacho et al., 2014; Olivier-Maget, 2007) Orantes Molina, 2005.</td></tr>
<tr><td rowspan="8">Isolation</td><td colspan="2">Localisation, Type (Nature), Time of Occurrence</td><td>Cause</td></tr>
<tr><td colspan="2">Fragkoulis, 2008.</td><td rowspan="7">Zhang, 2009
Anzurez-Marin, 2014.</td></tr>
<tr><td>Where: Location, Position, Area</td><td rowspan="6"></td></tr>
<tr><td>Patton, 1991; Gertler, 1988; Gertler, 1998; Simani, Fantuzzi, 2000; Palma et al., 2002; Palade et al., 2002; Ma, Jiang, 2011
Letellier, 2012Chen, Patton, 1999Poongodai, Bhuvaneswari, 2013.</td></tr>
<tr><td>Localisation (Classification)</td></tr>
<tr><td>Frank, 1996; Frank et al., 2000a; Capacho et al., 2014.</td></tr>
<tr><td>Which Element</td></tr>
<tr><td>Palma et al., 2002; Zhang, 2009.</td></tr>
<tr><td rowspan="2">Analysis</td><td rowspan="2"></td><td colspan="2">Type (Nature), Cause</td></tr>
<tr><td colspan="2">Frank, 1996; Capacho et al., 2014.</td></tr>
</table>

Table II.1 - Confusion between definitions of FDi constituents.

II.3.3 - Characteristics and Performances

An important aspect of *FM* system is its performance. Therefore, it is common in the literature to emphasize some important aspects for an ideal *FM* system. Some of them are related to *FDe*, while others are related to *FDi*. These characteristics and proprieties, according to *(Tarifa, Scenna, 2000; Venkatasubramanian et al., 2003a; Yu et al., 2014)* are: (*a*) *Speed (real-time) FDD* which is fundamental for a typical monitoring system. This implies that high computation and storage capacities must be provided. Furthermore, the modeling method should be low complex for quick and easy implementation. This requires a high and for fast real-time implementation of monitoring. (*b*) *Monitorability* considered as the most important feature of the system. (*c*) Ability to detect (*i.e.,* faults must be observable) and to predict the degree of criticality of the failure (important for the recovery function). *(d) Sensitivity* and *Robustness* of the system against *non-linearity,* various noise and modeling uncertainties. These involves the decrease of modeling discrepancies between the actual system and its model. This conducts to have *low FAl rates* and *fewer missed faults*. This feature gives an evaluation of a diagnostic system in terms of accuracy, efficiency and reliability *(Kiliç, 2005).* Practically, single *FDD* approach such as an analytical approach cannot eliminate the totality effect of errors and perturbation. *(e) Diagnostic resolution,* defined as being the *ratio* of the *number* of actual *defects* or *failures* by the number of *defects* or failures *diagnosed* by the diagnostic method being used; *(f)* Fine *isolability, identification* and *localization* of the fault. *Isolability* shows the capability of a diagnostic system to distinguish multiple failures. Isolating simultaneous faults is known as multiple fault *identifiability* which is the most difficult and significant requirements. (*g*) *Novelty idenfiability* is the capability to diagnose the system whether fault causes are from known or novel unknown malfunction. *(f)* Ability to identify multiple defects. (*h*) *Adaptability* or *portability* which is the ability to evolve against of new situations such as disturbances, variations in operating conditions, *etc*. *Adaptability* shows the capability of a diagnostic system to automatically response to system changes due to external inputs or structural changes. (*i*) *Explanation* gives clarification on where and how faults occur in a system which is required for on-line decision in control**.** Nevertheless, real monitoring systems typically have only a subset of these proprieties. More performances used for evaluating *FDI* and control performances are available in *(Prakash et al., 2002).* In practice, each proposed approach never satisfies all performances and the selection of *FDD* methodology is dependent on the behavior and feature of applications.

II.3.3.1 - Quick Detection and Diagnosis

Early, quick and accurate *FDD* system is an important, fundamental, and highly desirable attribute. However, the challenge in realizing it lies in the fact that quick response to *FDD* and tolerable performance during normal operation are two conflicting goals. Indeed, the system designed for fast *FDD* is sensitive to noise leading to frequent *FAl*s in even normal operations since some noise effect could be over the threshold. This one should be trade-off between the response speed and robustness (noise, *FAl* or threshold) *(Dash, Venkatasubramanian, 2000; Yu et al., 2014).*

II.3.3.2 - Storage and Computational Requirements

There is a trade-off between the computational complexity and system performance. Fast on-line decisions would require algorithms and implementations, which are less computationally complex, but might necessitate high storage requirements. A reasonable compromise between these two competing requirements is desirable *(Dash, Venkatasubramanian, 2000; Yu et al., 2014).*

II.3.3.3 - Monitorability, Observability and Chronicle

An important problem in runtime verification is *monitorability*. If a property is *not monitorable*, then it is meaningless to check it at runtime, as no satisfaction or violation will be reported in finite steps. A system is said to be *monitorable* if whatever the behavior of the system, we will be able to determine without ambiguity a unique monitoring**.** On other words, a system is said to be *monitorable* if it can be determined, using only (trajectories of) known variables, whether the system constraints are satisfied or not *(Blanke et al., 2003).* More details on *monitorablity* are given in *(Blanke et al., 2003).*

Observability is one of the important concepts that plays a central role in system theory. It is often necessary to obtain information on the state variables according to measurements of the inputs and outputs. In control theory, *observability* is a measure of how well internal states of a system can be inferred from knowledge of its external outputs. A dynamic system is observable if a state x of this system can be determined from an input sequence u and an output sequence y, both of a finite length *(Olivier-Maget, 2007; Patan, 2008).* On other word, A system is said to be state observable on a given time interval, if the states x can be determined from the system equations and the time histories of the input u and output y over the same interval *(Gertler, 1998; Kiliç, 2005).* Mathematically, a system represented by a system of state equations is fully observable if its observability matrix is equal to the dimension of its state vector *(Gertler, 1998; Olivier-Maget, 2007).* Furthermore, a system is said fully observable if each state variables affecting any of the outputs. If any state cannot be seen from the measurements of the outputs it is said that the system is not completely observable or simply unobservable *(Camacho et al., 2014).* In addition, fault observability means that the change of faults in a dynamic system can reflect itself in the change of measurements. More details on the observability can be found in *(Li, 2003; Fragkoulis, 2008; Jain, 2012).*

Another important characteristic of the system to be monitored is the *chronicle*, *i.e.* record or history of the sequences, which represents a group of signals associated to events of the system, and it defines a basic situation of a normal or abnormal change to be monitored. In addition, *chronicle* is represented as a set of events and a set of temporal constraints between these events, associated to *FDi* messages depending on topological constraints *(Taisne, 2006).*

II.3.3.4 - Robustness

An accurate model of a given system, for *Mathematical Model-Based Approach (MMBA),* cannot be obtained exactly. This can have different causes, such as an unknown disturbance structure, different noise effects and uncertain variables. Model uncertainty can cause either false or missed alarms. Hence, the quality of the used model and uncertainties about the measurements, influence negatively on the supervision mission *(Olivier-Maget, 2007).* Therefore, this uncertainty must be taken into account and some robustness procedures (*e.g.*, filtering) may be necessary to reduce their impact. If left untreated, it can have a serious impact and the *FM* system can become useless.

The robustness problem in *FM* can be defined as the *maximization* of the *detectability* and *isolability* of faults and simultaneously the *minimization* of uncontrolled effects such as disturbances, noise, changes in inputs and/or the state, *etc. (Chen, Patton, 1999).*

There are several approaches to deal with these aspects of robustness, divided into *active* and *passive (Chen, Patton, 1999; Puig et al., 2006)* as is shown on *Figure II.12.*

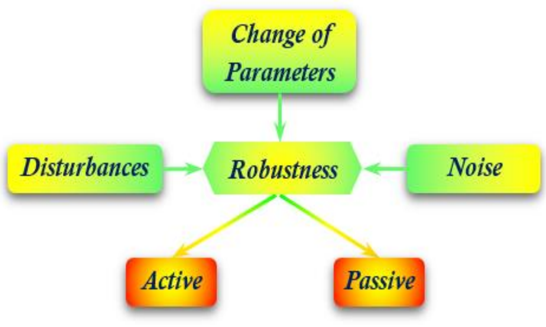


Figure II.12 – Robustness.

When the *MBA* is used, the *active robustness* approach deals with the uncertainty in the residual generation phase to avoid their effects. The *passive robustness* approach is applied during the evaluation of the residual and decision making. *(Fragkoulis, 2008).* Details of these approaches are given in *(Chen, Patton, 1999).* If a *FM* system satisfies robust feature, its performance should be insensitive to the effect of various noise and modeling uncertainties. The robustness should be traded-off between noise and the selection of a suitable *FDe* threshold to prevent frequent *FAIs* for normal operations. The approach such as state estimation for a dynamic system called *Unknown Input Observer* (*UIO*) can satisfy this feature because of its characteristic, which is not sensitive to the unknown inputs (disturbance and noise).

II.3.3.5 - Isolability

Isolability refers to the ability of the *FM* system to distinguish between multiple failures which sometimes overlap with noise and modeling uncertainties in terms of residuals. Therefore, there is a trade-off between *isolability* and the rejection of modeling uncertainties in an appropriate diagnostic system.
A classifier with a high degree of *isolability* would usually do a poor job in rejecting modeling uncertainties and vice versa.
We also desire *completeness, i.e.* actual fault(s) to be a subset of the proposed fault set. Resolution of a *FM* method would require the fault set to be as minimal as possible. Thus, there is a trade-off between *completeness* and *resolution* with respect to accuracy of predictions *(Dash, Venkatasubramanian, 2000; Yu et al., 2014).* More details on *isolability* are given in *(Blanke et al., 2003).*

II.3.3.6 - Novel Identifiability and Multiple Fault Identifiability

One of the minimal requirements of a *FM* system is to be able to decide, given current process conditions, whether the process is normal or abnormal and if abnormal, whether the causes are from known or novel unknown malfunction. This criterion is known as *novelty identifiability*.
On the other side, the ability to *identify multiple faults* is an important and difficult requirement for isolating simultaneous faults due to the interacting nature of most faults. Naturally, the combination of several faults typically occurs in *NL* or larger systems, leading to the difficult separation of individual fault. An *UIO* observer, which is in the form of state space equation and independent to disturbance, can capture uniquely fault signature and decouple faults. Moreover, the decoupling-based feature is another approach that is developed specially to isolate multiple faults *(Dash, Venkatasubramanian, 2000; Yu et al., 2014).*

II.3.3.7 - Adaptability

Processes in general change and evolve due to disturbances and variations in operating conditions. These latter can change due to changing environmental and operating conditions**.** Adaptability involves the capability of a *FM* system to adjust over time and to automatically response with system changes due to external inputs or structural changes. If the *FM* system satisfies adaptable capability, structural changes will gradually develop, as new environments, the scope of the system as new cases and problems emerge, as more information becomes available. Usually, *FM* systems designed by historical data or *KBAs* do not possess this feature since the limited scopes of data or approaches are specific or unchangeable *(Venkatasubramanian et al., 2003a; Yu et al., 2014; Marais, 2016).*

II.3.3.8 – Error Estimate

The evaluation of a diagnostic system can be performed through the *error estimate* in terms of accuracy and reliability to enhance the confidence of users. The *estimation error* feature shows the efficiency of diagnostic decisions. Practically, single *FDD* approach such as an analytical approach cannot eliminate residual errors. Even *UIO,* insensitive to unknown inputs or disturbance, tries to track the system until the residuals from disturbance are as small as possible. However, the errors from the estimation still occurring in the process due to noise, modeling uncertainties or linearization techniques.

II.3.3.9 - Explanation

Not only an *FM* approach can identify malfunctions, but also it should *explain* where and how faults occur and propagated in a system. Therefore, the *FM* system modeled with priori experiences has the ability of explanation and justify its recommendations. This feature requires the ability to reason about cause and effect relationships and is significantly useful for on-line decision support systems, the operator can therefore assess and act using his experience *(Venkatasubramanian et al., 2003a; Yu et al., 2014).*

II.3.4 - Applications

Accurate *monitoring* of the health state of systems, structures and components can contribute significantly to the safe and efficient operating of *NPP*s and allows a timely *detection* of malfunctions and anomalies**.** It provides plants with the information to evaluate *Instrumentation* and *Control* (*I&C*) sensors by providing applications that identify drifting instruments, alert plant personnel of unusual process conditions, and predict impending failures of plant equipment *(Hashemian, 2011).*
The *OLM system* gives plants the capability to verify the *calibration* of *pressure*, *level*, and *flow transmitters* as well as *Resistance Temperature Detectors* (*RTDs*), and *thermocouples*. It allows *detecting sensing-line blockages*, *testing the response time of pressure transmitters*, *monitoring the calibration of pressure transmitters on-line*, *cross-calibrating temperature sensors in situ,* and *extending the life of neutron detectors*. In addition, the *OLM system* encompasses other plant monitoring applications such as *assessing equipment condition*, *instrument calibration monitoring*, *instrumentation channel dynamic performance monitoring*, *performing predictive maintenance of reactor internals*, *monitoring coolant flow*, *identify sensing-line blockages*; *reactor core monitoring and alert the reactor operator of excessive vibration of reactor internals, Loose Part (LP) monitoring*, *Transient Identification (TI) (Ma, Jiang, 2011)* and *wastewater treatment process (Yoo et al., 2006; Fragkoulis, 2008; Fuente et al., 2012)*. In this section, some of these applications of *FM* methods in *NPs* are reviewed. *(Hashemian, 2011)* showed several *examples* of *OLM applications* in *NPs applications*. It also indicates whether the particular applications require *Alternative Current (AC)* signal, *Direct Current (DC)* signal, or both.

FDe and *FDi* applies to both the basic technical equipment and the actuators and sensors attached to it. Actuator and sensor *FDe* is very important because these devices are quite prone to faults. Sensors and actuators are vital components of any measurement and control system. Sensors inform the controller about its environment and the state of the system by providing the necessary measurements. With increasing of safety, performance, and automation requirements, control systems are increasingly sophisticated and are heavily reliant on their sensors. However, sensors are often considered as the weak link in these systems *(Balaban et al., 2009). FM* works presented by *(Böhme et al., 1999a)* constitute an important application of detection and reconstruction of sensor faults in a hydraulic purification plant. In addition, *digital I&C* technologies enable more cost effective data acquisition and management, which have created opportunities for *FDi*. For example, *sensors* and *actuators* can be programmed to perform self-validating *(Yang, Clarke, 1996; Tombs, 2001).* Industrial *Wireless Sensor Networks (WSNs),* are easier to set up, more flexible to relocate, and less expensive to deploy, as compared to a conventional *wired system*; thus, *WSN* provides an effective way to collect data for *FDi (Hashemian et al., 2011; Jiang et al., 2014; Oppermann et al., 2014). Equipment CM* of *NPP*s requires to optimally group the usually very large number of signals and to develop for each identified group a separate *CM model (Baraldi et al.,* *2011a). (Kang, Seong, 1995)* developed a core *internal vibration* monitoring system which is particularly concerned with the *Core Support Barrel (CSB)* in *ULJIN NPP* unit 1 in *Korea*.

II.3.4.1 - Instrument Performance and Calibration Monitoring

The *instruments* in a *NPP provide measurements* for plant monitoring, control and protection *(Ma, Jiang, 2012).* Various faults can potentially happen in instruments during plant operation, which can have significant impacts on plant reliability and availability *(Ma, Jiang, 2012).* Furthermore, the instrument in *NRs* are undergoing aging and their performance can degrade over time leading to problems such as drift and bias. Monitoring and calibration of instrument performance during plant operation is highly desirable to achieve *CBM*.

Critical process sensors and associated instrumentation in *NRs* are usually calibrated at each refueling outage. The calibrations are performed manually and involve two steps; each of which requires essentially the same work. The two steps are: (*a*) *Determine if calibration is needed*. This step is performed by providing the instrument with a series of known inputs covering the operating range of the instrument. The output of the instrument is recorded for each input and compared with the acceptance criteria for the instrument. (*b*) *Calibrate if needed*. If the instrument does not meet its acceptance criteria, it is calibrated by providing the same series of input signals as in *step 'a'* while adjusting the output to meet the acceptance criteria *(Hashemian, 1995).*

Prompt *FDe* and *FDi* which may arise on sensors and instruments is a topic of increasing interest for safe and efficient *NP* operation, and reliable and fault tolerant measurement and control systems *(Patton et al., 1989; Ma, Jiang, 2012).*

The remote access and verification of the sensors have been shown to limit the exposure of maintenance personnel to harsh environments while at the same time effectively and efficiently diagnosing the health and performance of these sensors. In addition to sensors, technologies exist in determining not only the health of *I&C* cabling that carries the signals from these sensors, but also these same cable testing techniques can be used in the remote evaluation of many end devices used in safety related operations as well *(Hashemian, 2009).*

A – On-Line Monitoring and Calibration

The procedure for *on-line calibration* tests involves calculating the deviation of each instrument channel from the best estimate of the process parameter that the instrument is measuring *(Hashemian, 1995).* This deviation is updated frequently while the plant is operating and plotted as a function of time for the entire fuel cycle. This provides time history plots that can reveal channel drift and other anomalies. Any instrument channel that exceeds the allowable drift or the channel accuracy band is then scheduled for calibration during a refueling outage, or sooner if necessary *(Hashemian, 1995).*

To deal with the performance degradation problems, *traditional periodic instrument calibration* is currently performed manually at a fixed time to almost all the instrumentation. *Periodic manual calibration of the instruments* is mainly the practice in the current instrument maintenance. This technique, consists of surveillance and adjustment *(James, 1997),* is used for *Signal Validation* (*SiV*), and it is vital to maintain efficient a plant operation.

However, *Periodic manual calibration* has many limitations. It is costly, time consuming (it takes an enormous amount of time), influence negatively on the availability, require a workforce specialized in the domain and in some cases involve radiation exposure to test personnel. Many periodic instrumentation calibrations are made out of service, require the instrument to be physically removed from the system, and can cause incorrect calibrations due to adjustments made in non-real conditions, and loss of product due to the system shutdown which is sometimes non-necessary. In addition, the hands-on calibrations can wear out the instruments and cause premature aging and damage *(Hashemian, 1995; Hines et al., 1996b).* In most case, the sensor is still within the allowed tolerances and intervention efforts were non-necessary. Operational experience shown that less

than 5% of sensors in a degraded condition that required intervention *(Hines, Seibert, 2006).* On other side, a drift occurring in instrument, between two consecutive time-based calibrations, may not be treated, although it is desirable to monitor the performance of the operation condition of devices throughout operation of the plant. This is referred to as *calibration monitoring* which can overcome the disadvantages encountered with the conventional method *(James, 1996).*
Therefore, the nuclear industry is *interested* in the *calibration reduction* (but not total elimination) by inter-comparison of redundant process measurements. *Calibration reduction,* a *particular application of SeV,* does not eliminate the need to perform instrument calibration, but lessens the effort involved *(Holbert, Lin, 2012).* In a *NR*, calibration reduction can lower the amount of time spent in radiation areas, thereby reducing personnel exposure *(Holbert, Lin, 2012).*
In addition, the nuclear industry is *interested* in *automating the calibration* of the *instruments* and has sponsored a number of research projects to determine the validity of automated calibrations *(Hashemian, 1995).* The *advantage* of *automated calibrations* is that they provide the opportunity to test the calibration of instrument channels on a continuous basis. This improves the safety and efficiency of the plant while reducing the cost of the calibrations and eliminating much of the personnel radiation exposure associated with conventional calibrations *(Hashemian, 1995).*

OLCM is the monitoring of normal *process instruments* during plant operation and comparing the data with an estimate of the process parameter that the instrument is measuring. The process parameter estimate may be obtained using *a variety of methods*. The *OLCM* techniques are typically performed during steady state conditions (*i.e.,* constant process operating conditions).
However, in order to verify the *calibration of instruments* over their entire operating range, *OLM* data should be collected at various operating conditions *(Hashemian, 2009).* An obvious benefit of *calibration monitoring* is reduced manpower requirements due to the lessened workload. *(James, 1997)* gave a comparison of conventional calibration program and *OLCM* methodologies.
OLCM techniques are designed to continuously assess the performance of certain instruments by assessing their mutual consistency with references. They refer to monitoring the normal output of instruments during plant operation and comparing the data with an estimate of the *System/Process* (*S/P*) parameter that the instrument is measuring to identify *drift*. If drift is identified, then the sensor is calibrated. For determining the best estimate of the process, the parameter estimate may be obtained using a variety of methods and sometimes complementary. These methods are: (*a*) simple and weighted averaging of redundant signals, (*b*) empirical and physical modeling, (*c*) *NNs*, and (*d*) a reference channel that is calibrated before and after each fuel cycle *(Hashemian, 1995; Hashemian, 2005).*

In *Hardware Redundancy (HR),* redundant physical sensors are used to measure one variable output from redundant sensors and can serve as references for cross-checking each other. This is the basic idea of the *cross-calibration technique* *(Hashemian, 2006),* where the average of a set of redundant sensors is considered to be the true value of a variable being measured. Signals that fall too far away from the other redundant signals are excluded from the average or are weighted less than the signals that agree well with each other. With this method, redundant sensor outputs are monitored during process operation. A fault in a sensor can be detected if the sensor shows any abnormal deviation or drift with respect to the process parameter estimate (*e.g.,* average). If the sensor drift is outside of prescribed limits, the sensor is re-calibrated. Otherwise, the sensor is not calibrated or calibrated less often. The averaging technique has been able to pass regulatory licensing requirements for safety-related applications and be commercially applied in the nuclear industry. This method is applicable to all types of process sensors; however, the best application is for calibration verification of pressure, level, and flow transmitters *(Roverso et al., 2007; Hashemian, 2009).*

However, drawbacks of *HR* lead to the use of other methods, mainly *Analytical-Based Technique (ABT)* and *DDT* are more practical options. Plant monitoring systems developed based on these *calibration monitoring* methods have been implemented in a number of plants *(Fantoni, 2005; Hines, Davis, 2005).*
A *redundant analytical sensor* can be created by using modeling techniques used as a reference for *detecting drift*. A fundamental knowledge of the process and material properties is often required to provide reliable estimates of a parameter using a physical model. As such, *empirical models* are often preferred for parameter estimation for *on-line tracking* and *calibration drift verification (Hashemian, 2009).*

B - Neutron Detectors

Effective managing of the aging of neutron detectors depends to some degree on the detector manufacturer and the strategy of the *NP* for verifying the performance of nuclear instrumentation systems. Some manufacturers recommend that detectors be replaced as often as once every 5 years; other manufacturers state that their neutron detectors can be used for as long as 40 years if they are in good working condition. In the latter case, manufacturers sometimes recommend cable testing and static and/or dynamic performance monitoring as a way to check that the neutron detectors are in good working condition. The response time of the detectors increases during the first two decades and then stabilizes. This is expected of neutron detectors as well as other sensors *(Hashemian, 2011).*
In addition to the ability to check the health of the detector itself, the *noise output of neutron detector* can be examined for *signs* of other *problems in the nuclear instrumentation circuit*, such as cable and connector anomalies. *(Arndt, Miller, 1991)* showed the *Auto-Power Spectral Density* (*APSD*) of a neutron detector before and after the onset of a cable degradation problem. In this case, analyzing the *APSD* reveals a difference in the neutron detector dynamic response resulting from an increase in cable capacitance.
CtM of neutron detectors can reveal problems in the neutron detector circuit, enabling plant personnel to schedule maintenance accordingly *(Hashemian, 2011).*

C - Sensor

Sensors provide the means by which operators and control regulate systems. The performance of these *sensors* such as *thermocouples*, *thin-film RTDs*, *strain gages*, and other resistive devices that are used in *NP*s for measurement of surface conditions of pipes, vessels, and other components should be checked. In these applications, the *sensors are bonded to a solid surface*. Years of research, testing and experience in the field of sensor *FDi* have yielded many technologies which offer financial as well as operational benefits to the nuclear industry. Diagnostic functions and *CM* must be performed based on *validated process sensors*. *SeV* is a determination whether a process indicator is providing a reliable reading. The process readings are monitored on a continuous basis. During this time period either the signals will agree or they will disagree. The incentives for performing *SeV* lie in both concerns for safety and the economic returns possible. Properly *validated signals* increase plant availability and the reliability of operator actions *(Holbert, Lin, 2012).*
Sensor malfunction, or just *de-calibration*, can also occur under much less dramatic circumstances, through *fouling*, *incipient*, *drift*, *response-time degradation*, and *aging (Hashemian, 2011). Two primary types of failure* are addressed by *SeV*: (*a*) *incipient* (*catastrophic*) *failure detection* and (*b*) *detection of instrument calibration drift*. Many methods originated from the aerospace and nuclear industries have been developed to perform *signal validation*. Most techniques employ a two-stage process: (*a*) *generation of residuals* and (*b*) *decision making* based upon hard thresholds. The *decision making* is based upon various tests, including the *generalized likelihood ratio* (*GLR*), *sequential probability ratio test* (*SPRT*), and *innovation properties* (tests for *whiteness*, *mean*, *covariance*, *chi-square*, *etc.*), applied to the residuals *(Holbert, Lin, 2012).*

Dynamic performance is an important aspect of instruments in *NPs*. For sensor, response time is very important particularly for safety systems**.** It is well known that the response time of sensor such as *RTDs* and *thermocouples* is subject to change over time. For these and other reasons, *response time* of *RTDs* and *thermocouples* is measured periodically in *NP*s (*Figure II.13*). *Response time* can be defined as the time taken by the sensor output to reach 63.2% of its final steady-state value following a step-change in the input. Other definitions of response time are also used, such as "the time to reach 90% of the final output" or "the time required for the sensor output to go, for example, from 10 percent to 70% of its final value".

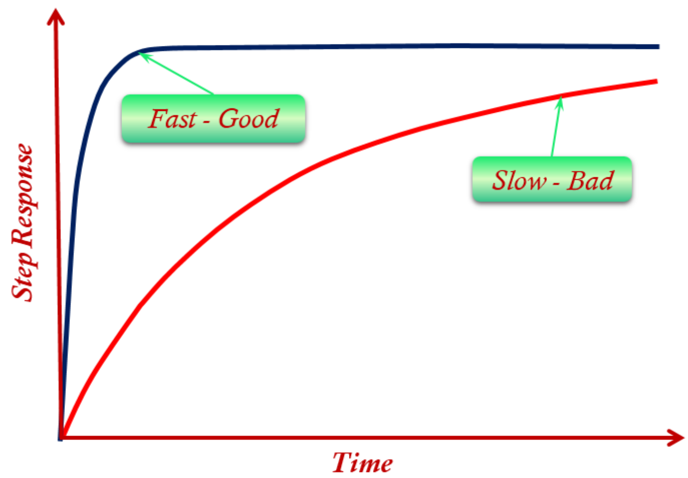


Figure II.13 - Response Time Data for a Slow and Fast RTD (Hashemian, 2009).

The time constant of an instrument should not exceed the maximum value assumed in the safety analyses. To describe the response time of a sensor, a variety of terms are used, such as *time constant*, *break frequency*, or the time required for the sensor's output to go from one value to another. The term *break frequency* is used to describe the response speed of a sensor in terms of a frequency, and other terms such as *corner frequency*, or *frequency response* are often used. However, the degradation of response time of an instrument still encountered in systems of plants and many factors contribute to this *degradation*. The *response time* of *NP* temperature sensors is predominantly affected by *environmental conditions* such as *fluid FR* and *temperature*, *installation into a thermowell* (when it is used), and degradation due to aging. *Temperature* variations can result in changes in sensor *response time*. For example, a temperature sensor's response time decreases as the heat-transfer coefficient is increased and inherent voids in *sensor insulation materials* can expand or contract and cause the *response time* to change. Furthermore, *vibration* can cause *RTDs* and *thermocouples* to move out of their thermowell and result in an increase in *response time*. Even a very small movement can cause a large change in response time. Testing the response time of an instrument often requires taking it physical out of service. Unfortunately, this operation (off-line tests) cannot replicate the exact real operating conditions. Furthermore, it is very difficult and expensive to carry out these tests frequently. The *transfer function* of a system or instrument can be used to determine the *dynamic response* and identify the system's *response time* to any input such as a step, a ramp, or a sinusoidal input. *Signal analysis* methods in both *time* and *frequency domains* can be used to extract *response time* from the measurement noises. In the, the *Power Spectral Density (PSD),* of the measurement noises is first obtained from which the *time constant* can be estimated as the inverse of the break frequency. For *pressure transmitters*, depending on which pressure test signal is selected, three methods are available for testing the *response time*: *ramp test*, *step test* and *frequency test*. There are two other methods available for *in-situ* testing of *pressure transmitters' response times*: The *Noise Analysis* (*NA*) *technique* and the *Power Interrupt (PoI) test*. The *NA technique* is used to remotely *measure sensor response time* from the control room area while the plant is on-line. These measurements do not require the sensors to be disconnected from the plant instrumentation or removed from service for the tests. That is, the tests are passive and do not cause any disturbance to plant operation. This reduces test time and helps to reduce radiation exposure of the test personnel who would otherwise have to enter the reactor containment to make the response-time measurements *(Hashemian, 2011)*. The *PoI* test can only be used to test the *response times* of *force-balance pressure transmitters*. In any case, degradation of dynamic response can be diagnosed by comparing the recently computed response time with what is considered to be normal. For more details, the *NRC Regulatory Guide* 1.118, *NUREG*-0800, and *NUREG*-0809 all relate directly or indirectly to sensor *response-time testing (Hashemian, 2005, Hashemian, 2006, Hashemian, 2009).*

D - Sensor Noise Analysis

The *NA technique* can be used for evaluating the health and reliability of *NP sensors*, *processes*, and *equipment* from data acquired while the plant is operating. For the sensor, *NA* provides a mean for dynamic performance monitoring based on monitoring the natural fluctuations that normally exist on the output. While the process is operating normally, the sensor's output would have a steady-state value corresponding to the process indicated by the sensor. This steady-state value is often referred to as the *DC* value. On top of the steady-state value, *noise-like fluctuations* often exist at the outputs of a sensor (*Figure II.14*). Because the *static* and *dynamic components* of the sensor output each contain different information about the process being measured, they can be used for a wide range of monitoring applications.

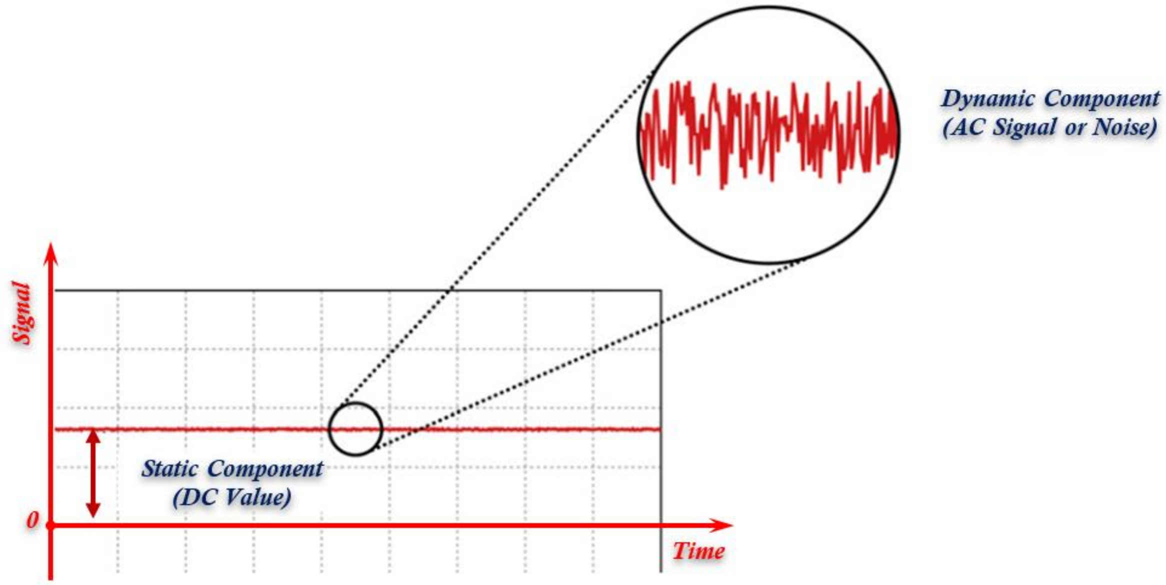


Figure II.14 - Normal output of a process sensor with illustration of the DC and AC components of the output (Hashemian, 2011).

In *NPP*s, the output fluctuations of process sensors are due to random flux, random heat transfer, turbulence, vibration, and other mechanical and thermal hydraulic phenomenon. The *NA* technique has already become an important diagnostic tool for *sensor health analysis* in *NPs* by differentiating between sensor degradation and system malfunction *(Hashemian, 2011)*. Fluctuations (noise) can be extracted from the sensor output and analyzed to yield the sensor's response time. It can be used for the *in-situ response time* testing of *pressure*, *level*, and *flow transmitters*. For *temperature sensors*, a number of techniques, collectively referred to as *in-situ* and/or *on-line testing*, have been developed to verify the calibration and response time while these sensors remain installed in an operating process. For example, the *Loop Current Step Response* (*LCSR*) test has been developed for verifying the dynamic response of *RTDs* and *thermocouples* as installed in an operating process. Therefore, the *LCSR* method is the most commonly used technique because it can yield a *sensor's response time* so accurately *(Hashemian, 2005)*. *NA* has also been studied for on-line determination of *prompt fractions* of *Self-Powered Neutron Detectors* (*SPNDs*) in *Canada Deuterium Uranium (CANDU)* reactors. It is based on the understanding that only

the prompt signal of a *SPND* is able to follow the neutron flux fluctuation around 0.25 *Hz* in the reactor caused by reactor regulating systems *(Demazière, Glöckler, 2004)*.
Furthermore, the condition of a *NP* can be effectively monitored by analyzing these small fluctuations in the process variables, such as ρ coefficients, vibration amplitudes, and response times, around their stationary value.

The advantage of the *NA* technique is that it does not require that the sensor be removed from service, and many sensors can be tested simultaneously using a single multichannel noise data acquisition system *(Hashemian, Jiang, 2010).*

The *types of OLM applications* used in *NPP*s are in large part *determined by the sampling rates* available for data acquisition. *Static OLM applications*, such as *RTD* cross-calibration and *OLCM* of *pressure transmitters*, typically require sampling rates up to 1 *Hz*, while *dynamic OLM applications* such as sensor response-time testing use data sampled in the 1 *kHz* range. Other, *high-frequency OLM applications*, such as measuring the vibration of rotating equipment and monitoring *LP*s, may use data sampled at up to 100 *kHz*. *I&C* sensors that measure temperature, pressure, level, flow, and neutron flux up to data sampling frequencies of around 1 kHz represent the majority of measurement devices in *NPP*s *(Hashemian, 2011).*

E - Instrument channel

An *instrument channel* consists of a *sensor* that is located in the field, signal conversion, *signal conditioning*, and logic and trip circuitry that are located in instrument cabinets in the *control room* or cable spreading room areas of most *NPs*. The *sensor* could be a pressure, level, or flow transmitter, a *RTD* that is used for measurement of reactor coolant hot leg or cold leg temperatures, a core exit thermocouple, a neutron detector, *etc*. *OLM* can *identify drift* in a *sensor* such as a *pressure transmitter* or an *entire instrument channel* (except for the actuation system) depending on where the *OLM* system is connected to the instrument channel. The components of *instrument channels* beside the sensors are *calibrated manually* during each refueling outage by making necessary adjustments to ensure that the component has the desired output (steady-state output) and to determine if the channel is drifting beyond an acceptable limit. These components are calibrated individually or together depending on the instrument channel design and the plant requirements. A calibration test signal is injected into each component or a group of components. It should be pointed out that the calibration of some process signals such as the high pressure coolant injection flow in *BWRs*, which are normally off-scale during plant operation, cannot be tested on-line. Therefore, the instrument channels for these signals must continue to be calibrated manually using the conventional procedures. However, the number of instrument channels that cannot be tested on-line is much smaller than the number of instrument channels that are testable during plant operation *(Hashemian, 1995).*

Some researchers have promoted *FL* in the context of *instrumentation FDe*. Application of *FL* to *signal validation* appears to have been first proposed by *(Heger et al., 1993)*. As they stated, *fuzzy logic* (*FL*) is useful for *instrument FDe*, as it possesses the advantage of transforming linguistic information to numerical values for processing and then later back to the linguistic domain *(Holbert et al., 1994; Heger et al., 1996)*. *(Mourot et al., 1993)* suggested the use of *fuzzy pattern recognition* for *gross error detection problems* as may be encountered when utilizing parity equations to generate residuals. *(Sauter et al., 1994)* investigated the use of *FL* to *diagnose sensor* and *actuator faults* in a simulated mechanical system. In particular, they evaluated residuals in an adaptive manner, and they used an FL technique to diagnose fault signatures from a *Dedicated Observer Schemes (DOS)*.
In addition, *(Hines et al., 1997b)* used *FL* to model and estimate process states as part of an adaptive *neural-fuzzy* inference system intended to perform *instrument channel calibration verification*. Other hybrid implementations of *FL* for *SeV* include the coupling of *FL* with state estimation techniques *(Lin, Holbert, 2005)*.

F - Valve

Acoustic Emission (AE) monitoring has been studied for diagnostic applications such as leakages in pressure boundaries *(Kunze, 1999),* bearing damages *(Li, Li, 1995),* valve wear *(Lee et al., 2006a),* and faults in rotating machineries *(Neill et al., 1997)*. *AE sensors* used for the *Valve Flow Monitoring* are mounted on or close to the key valves in the plant which are to be monitored. These sensors detect the frequency components of the sound and convert them into electrical signals *(Vahaviolos, al., 2008)*. *On-line AE monitoring* of *valves* can detect *leakage* and *anomalous valve noise* from sources other than leakage, and monitor *the valve opening* (for some types of valves) *(Rhodes, Langenberg, 2012).* Indeed, *On-line AE monitoring* has been used on *check valves*, *needle valves*, *control valves*, and *safety relief valves* *(Nakamura et al. 1985; Tsunoda et al. 1985; Haynes, 1990)*. Furthermore, *higher frequency AE sensors* are used on *turbulent flow* or *leak* in *the valve* *(Vahaviolos, al., 2008).*

The major advantage of *AE* technique over others is instantaneous notification of aberrant conditions. Further, leak detection is not limited to leaks across the valve seat or leaks through the pressure boundary. *AE monitoring* can detect any leak that generates significant turbulence as fluid passes through an area of restricted flow *(Rhodes, Langenberg, 2012).* Finally, when used in conjunction with other techniques, *AE* monitoring can provide more complete information about the operation of the valve (*e.g.*, *position* and *motion* of valve internals and estimates of *FRs* and *leak rates*) *(Haynes, 1990).* Other techniques that can enhance *AE* leak detection include *ultrasonic inspection*, *magnetic flux signature analysis*, and *external magnetic excitation methods*.

G - Cables

In many commercial plants, not limited to *NPs*, safety-related cable splices are used to provide electrical connections. However, the cable splices are vulnerable to the environmental stresses such as *thermal*, *mechanical*, and *chemical factors* that is unavoidable. Usually in *NP*, instrumentation cable and splice are installed on the tray, which are located at the vicinity of coolant pipes and pump motors. These stressful environments induce the aging of cables splices. Therefore, environmental qualification and evaluation of aging for safety-related cable have been performed *(Lofaro et al., 2001; Villaran, Lofaro, 2002).*

Varieties of *CM* techniques for instrumentation and cable splices have been developed and can be categorized by *thermal* and *electrical techniques*. Examples of *thermal CM* techniques are visual inspection and *Infrared Thermography (IRT),* which are inexpensive and easy to perform. However, the applications of *thermal CM* techniques are limited to cables physically accessible for inspection, which may not be available for real world *(Villaran, Lofaro, 2002).* On the other hand, a *dc high voltage testing*, a *dielectric loss/power factor measurement*, and a *Time-Domain Reflectometry* (*TDR*) are *electrical CM* techniques used in power generation plants. The *dc high voltage testing* may induce damages on insulation materials of cables due to the dc high voltage for testing and since it cannot locate the bad splices in cables.

TDR technique is based on the *reflection phenomenon* of *electromagnetic wave* at the impedance discontinuity in cables *(Hashemian, Bean, 2011; Hashemian et al., 2013; Shi, Kanoun, 2014).* If an incident signal, such as a step signal, is sent through cable, the incident signal is reflected back to the measurement point at any impedance discontinuity. The reflected signal will show any changes in impedance along the cable, including at the end of the cable. If the *TDR* is trended, problems that may develop along the cable or at the end device can be identified and located. Therefore, theoretically, *TDR* can detect and locate defects from the time delay between the incident and reflected signals. *TDR* is used to *locate problems* along a *cable*, in a *connector*, or at an *end device* by sending a test signal through the conductors in the cable and measuring its reflection. The *TDR technique* has also served the *Pn* industry in *testing instrumentation circuits*, *motors*, *heater coils*, and a variety of other components *(Hashemian, 2009).*

However, applications of *TDR* is susceptible to ambient noise, so high level of training or experiences are required to analyze the states of cable splices from *TDR* measurements in real world *(Shin et al., 2005; Wang et al., 2010; Wang et al., 2011).* Another drawback of *TDR* is that range resolution and average transmitted power related with the *Signal to Noise Ratio* (*SNR)* of receiver depend on the time duration of the incident signal *(Mahafza, 2013).* Thus, the tradeoff relation between range resolution and average transmitted power exists.
A *compressed pulse* such as chirp signal and the matched filter receiver are used to resolve the limitations of *TDR* by improving both the range resolution and the average transmitted power in reflectometry *(Mahafza, 2013)*. Furthermore, *Time–Frequency Domain Reflectometry* (*TFDR*) uses a Gaussian enveloped linear chirp signal, and a normalized time–frequency cross correlation to improve the range resolution and the average transmitted power simultaneously *(Shin et al., 2005; Wang et al., 2010; Wang et al., 2011)*.
(Chang et al., 2015) proposed the *linear chirp reflectometry* with *chirp stretching processing* To locate and diagnose the *splice* and *varieties of faults* in the *instrumentation cables*. The *chirp stretching processing* converts the time delay to the instantaneous beat angular frequency, and it also converts the splice localization problem to the time-varying spectrum estimation problem.
The combination of *TDR*, *Inductance–capacitance–resistance* (*LCR),* and *Loop Current Step Response* (*LCSR)* tests has proved very effective in separating cable problems from sensor problems in *RTDs*, thermocouples, and strain gauges. As for other *NP* sensors such as neutron detectors, the combination of *TDR*, *LCR* and the *NA* technique are used to verify the integrity of the cables and performance of the end device, in this case, the neutron detector *(Hashemian, 2009).*

II.3.4.2 - Equipment Condition Monitoring

Normal operation of *NP*s depends on satisfactory operation of many components, particularly electrical machines to drive *fans*, *chillers, pumps*, *diesel generators*, and *compressors*. Electrical machinery is the powerhouse of the modern industry and operational interruptions of these equipment may lead to economic losses. Rotational equipment, rotating electric motors, electric motors, or simply motors are a workhorse which play a pivotal role are widely used in most industries (*e.g.*, oil refinery, pump oil, steel mill, mine, compressor and power plants, and they are critical components *(Goutam, Sathish, 2018; Sangeetha, Hemamalini, 2019).*
An *electrical machine* converts input electrical power to output mechanical power and the difference between them is considered as losses *(Singh et al., 2016a).* Most electric motors operate through the interaction between the motor's magnetic field and electric current in a wire winding to generate force in the form of torque applied on the motor's shaft. Electric motors can be powered by *DC* sources, such as from batteries, motor vehicles or rectifiers, or by *AC*. An *electric generator* is mechanically identical to an electric motor, but operates with a reversed flow of power, converting mechanical energy into electrical energy.
Electric motors may be classified by considerations such as power source type, internal construction, application and type of motion output. In addition to *AC* versus *DC* types (*Figure II.15*), motors may be *brushed* or *brushless*, may be of *various phase* (see *single-phase*, *two-phase*, or *three-phase*), and may be either air-cooled or liquid-cooled.

A *DC* motor is any of a class of rotary electric motors that converts *DC* electrical energy into mechanical energy. *DC* motors are easy to control and a speed of a *DC* motor can be controlled. *DC* motors are used in propulsion of electric vehicles (for example trams), hoists and elevators. Small DC motors are used in various tools such as: printers, hard disks and *CD/DVD ROM* drives *(Glowacz, 2016a).*
An *AC* motor is electric motor driven by an *AC*. The *AC* motor commonly consists of two basic parts, an outside stator having coils supplied with alternating current to produce a rotating magnetic field, and an inside rotor attached to the output shaft producing a second rotating magnetic field. The rotor magnetic field may be produced by permanent magnets, reluctance saliency, or *DC* or *AC* electrical windings. The main types of *AC* motors are *synchronous motors, asynchronous motors* known also as *Induction Motors* (*IMs*) and *linear* (*Figure*

II.15). The *IM* always relies on a small difference in speed between the stator rotating magnetic field and the rotor shaft speed called slip to induce rotor current in the rotor *AC* winding. The *synchronous motor* produces its rated torque at exactly synchronous speed. The motor which produces the linear force instead of the rotational force is known as a *linear motor*. This motor has unrolled rotor and stator. Such type of motor is used on sliding doors and in actuators. *IMs* (*Figure II.16*) are most commonly used prime mover among electrical motors. The *single-phase IM* is one of the types of *IM* *(Glowacz et al., 2017),* simple in construction, inexpensive and reliable. The *three phase IMs* are most widely used as the prime movers and the main electromechanical energy conversion device in all industrial applications *(Eftekhari et al., 2013, Singh et al., 2016a).*

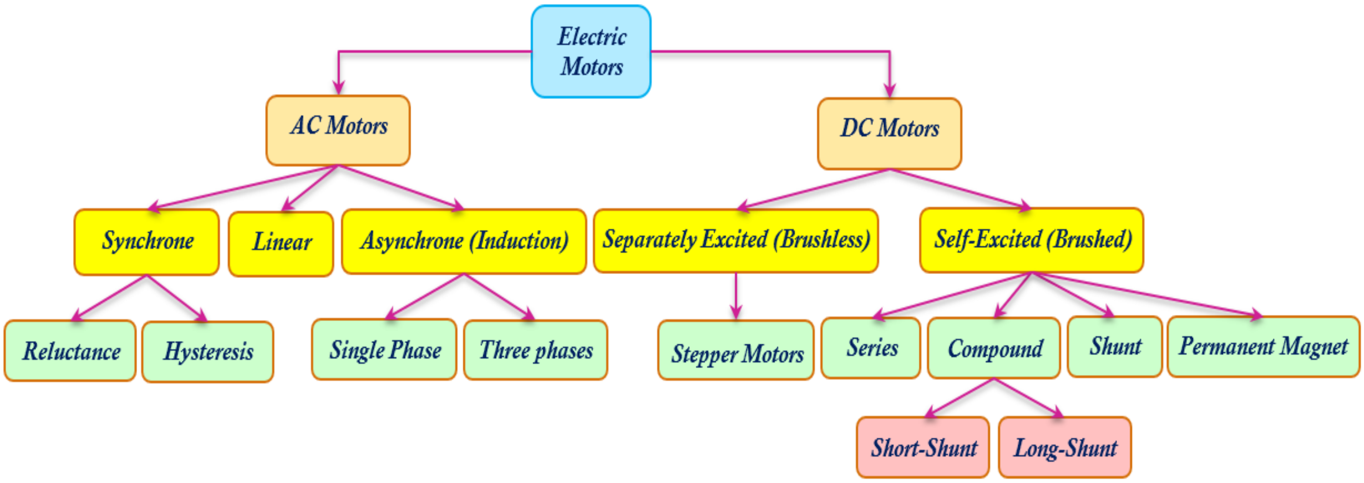


Figure II.15 – Types of electric motors.

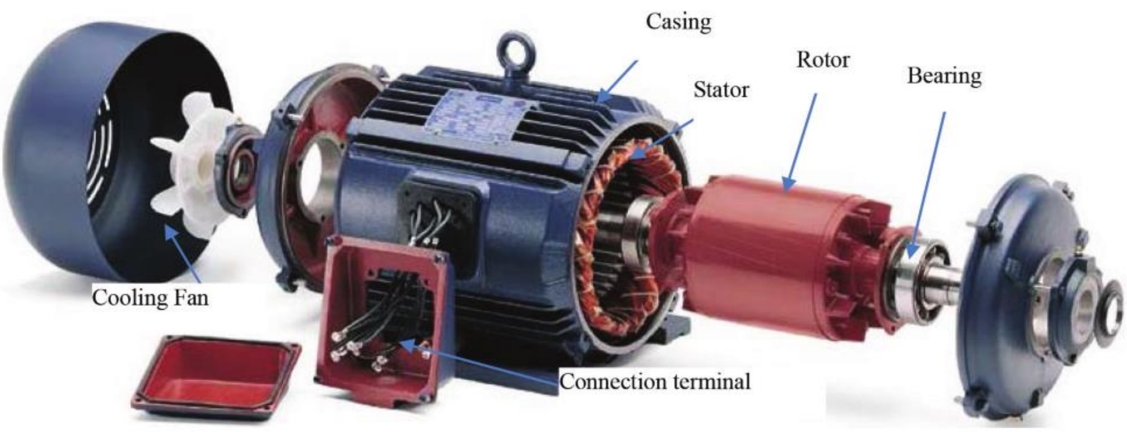


Figure II.16. Structure of IM (Irfan et al., 2017).

A - Faults

Under *Normal Operating Conditions (NOCs)*, *electrical machines* might fail because of wearing down associated with their operation *(Hurtado et al., 2015).* Many parts of the motor (rotor shaft, bearings, insulation, stator and rotor circuits) wear out depending on operating stress and operation time *(Glowacz, 2019).* Various faults and malfunctions can occur in electrical machines such as unbalance, excessive radial load, rotor-to-stator rubbing, fluid induced vibrations, and loose stationary and rotating parts, coupled torsional-lateral vibration excitation, and rotor cracking *(Kumar, Kumar, 2014).* Majority of faults are *bearing* and *winding* related. The *winding failure* is considered serious. It increases stress on the winding insulation, which has a potential to completely damage the motor, if left untreated. *Inter turn fault* is also most commonly observed faults in the motors and is considered the most severe. It can lead to the failure of complete phase and can even cause accidents, if left undetected or untreated *(Singh et al., 2016b).* Several surveys *(Sin et al., 2003; Puche-Panadero et al., 2004; Miljkovic, 2015)* have found the *most common failure mechanisms* are classified according to the main components of a machine: faults related to *stator, rotor*, *bearings* and *eccentricity* or any combination of these faults. Almost 80% of common rotating equipment problems are related to misalignment and unbalance *(Mortazavizadeh, Mousavi, 2014).* In addition, the other most common *rotor faults* in an *induction machine* are *broken bars*, *rotor eccentricity* and *winding faults (Sangeetha, Hemamalini, 2019).*

The major faults of electrical machines can broadly be classified by the following *(Korde, 2002; Thomson, Gilmore, 2003)* : (*a*) Static and/or dynamic air-gap irregularities, (*b*) Broken rotor bar or cracked rotor end-rings, (*c*) Stator faults (opening or shorting of one coil or more of a stator phase winding), (*d*) Abnormal connection of the stator windings, (*e*) Bent shaft (akin to dynamic eccentricity) which can result in a rub between the rotor and stator, causing serious damage to stator core and windings; (*d*) Bearing and gearbox failures.

The reasons why machines are subjected to degradation and fail during operation in industry are due to *external, internal conditions,* operating stress and operation time (*Figure II.17*). *External conditions* (*Figure II.18a*) are mechanical (*e.g.*, load variation, overload, assembly wrong), electrical (*e.g.*, transitory and voltage fluctuation, connection and installation wrong, voltage imbalance), environmental (moisture, thermal stresses, pollution) which lead to several faults in different parts of the machine. *Internal faults* (*Figure II.18b*) can be classified with reference to their origin. They can be *mechanical* (*e.g.*, Sheet and coils displacement, bearing fault, dynamic, static eccentricity) or *electrical* (insulation fault, break of rotor bars, magnetic circuit fault) *(Bazurto et al., 2016; Sangeetha, Hemamalini, 2019).*

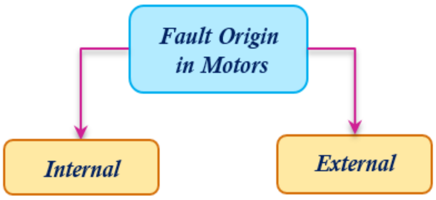


Figure II.17. Faults origin in motors.

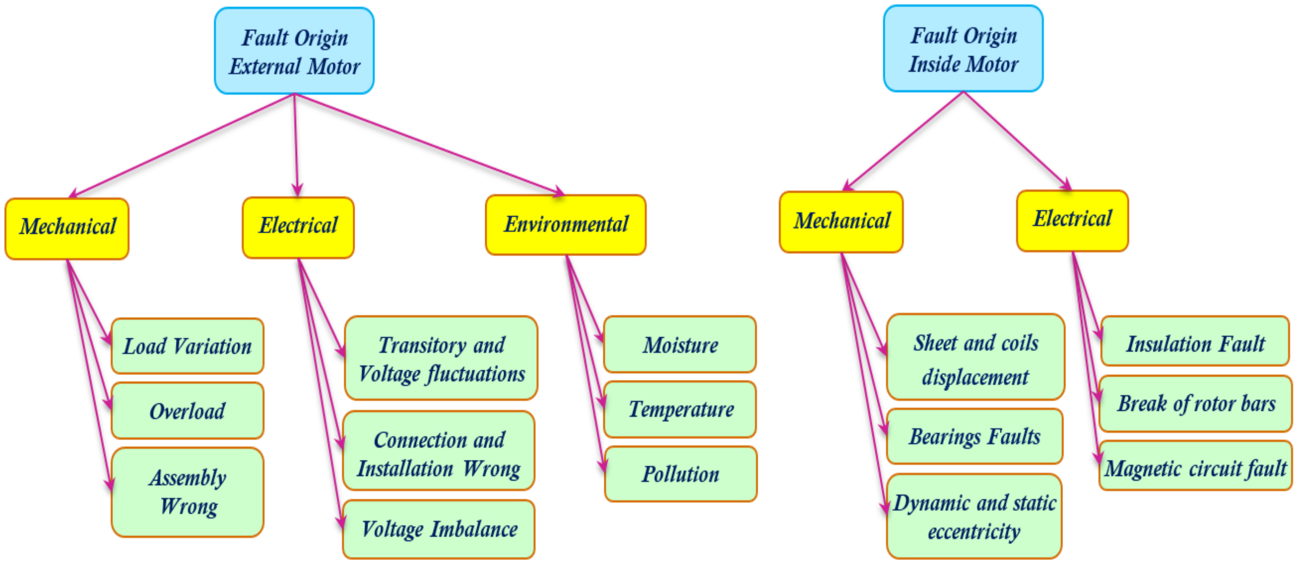
(Irfan et al., 2017) reported some commonly reasons why electric motors fail in industry as follows : (*a*) Wrong-rated power, voltage and current; (*b*) Mistakes during repairs; (*c*) Unstable supply voltage or current source; (*d*) Post the standard lifetime; (*e*) Overload or unbalanced load; (*f*) Electrical stress from fast switching inverters or unstable ground; (*g*) Residual stress from manufacturing; (*h*) Harsh application environment.

Internal faults can be also classified with reference to their location: *stator* or *rotor (Figure II.19).* Several studies as *(Nandi et al., 2005; Siddique et al., 2005)* are agree in classify, the *rotor* and *stator* failures as a combination of several forces acting on each of these components.

In the *Table II.2*, a classification of these factors is presented *(Bazurto et al., 2016). Stator core faults* are caused by *loosely core*, *sticking core laminations* (failure of core insulating layer) and *rotor shock*. *(Lee, Habetler, 2007)* classified faults in *permanent magnet synchronous motor* (*PMSM*) into *electric*, *magnetic* and *mechanical faults*. The most common *mechanical fault* in *rotor* is *eccentricity* (*static* and *dynamic*), other *mechanical faults* include *rotor rubbing* and *stator* and *rotor fatigue*. *Winding faults* such as inter-turn, coil-to-coil, phase-to-phase and winding-to-earth are the origins of *electric faults* in *PMSMs (Faiz, Exiri, 2015).*

Common machine faults in *rotor* according to *(Singh, Al-Kazzaz, 2003)* are machine faults in rotor: (*a*) Bearing; (*b*) failure; (*c*) Rotor broken bars; (*d*) Rotor body failure; (*e*) Bearing misalignment; (*f*) Rotor misalignment; (*g*) Bearing loss of lubrication; and (*h*) Rotor mechanical or thermal unbalanced. On the other side, common faults become apparent in *stator* are: (*a*) Frame vibration; (*b*) Stator earth faults; (*c*) Damage of insulation; (*d*) Stator turn-to-turn faults; (*e*) Stator phase- to- phase faults; (*f*) Displacement of conductors; and (*g*) Failure of electrical connections *(Mortazavizadeh, Mousavi, 2014).*

According to some survey reports, the percentages of failure occurrence statistics of various components in *IMs* are: *bearing* (41%) (Sangeetha, Hemamalini, 2019), *winding* (37%), *rotor faults* (10%) (Skowron et al., 2019b) and *others* (12%) (Singh et al., 2015; Verucchi et al., 2008) (Figure II.20). However, it is known that failures depend on the type of electrical machine, working conditions, where are located, as well as the duty cycle to which they are subject (Hurtado et al., 2015).



(a) External *(b) Internal*

Figure II.18. Classification of motor fault sources (Bhowmik et al., 2013).

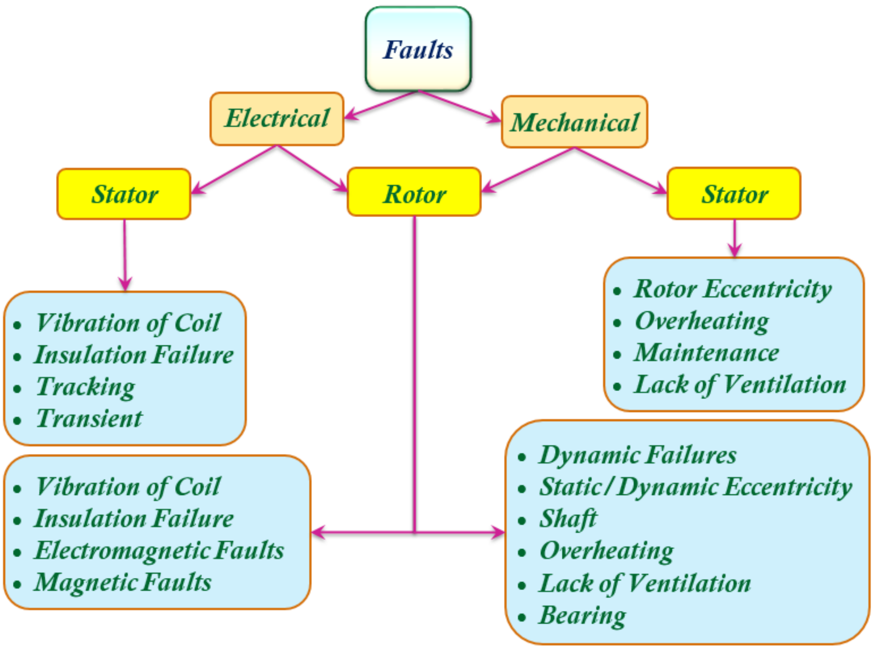


Figure II.19 - Types of failures in electrical machines according to their location; stator or rotor (Irfan et al., 2017).

The various environmental, thermal and load constraints to which the machines are subjected, ultimately reduce the efficiency of the engine and later lead to failure. Any degraded part and fault in these machines, may yield a complete shutdown of the equipment during the operation or an unexpected interruption in the industrial plant with consequences in costs, product quality, and safety. Furthermore, failure of motor in critical applications can lead to high production loss and in some cases can results in fatal accidents. Failures in *machinery*, in most cases, do not appear untimely manner but rather develop gradually along the time instead as a sudden failure. This makes possible to detect a failure during the earlier stages before its consequences become catastrophic. Repair or replacement of a damaged motor costs time and money. Often it is better to repair the motor than replace it, particularly, if it is an expensive. Faults in *IMs* lead to poor efficiency *i.e.,* more energy consumption *(Frosini, Ezio, 2010; Arabaci et al., 2014)*.

Stator	*Stress thermal (Aging, overload, work cycles)*
	Stress electric (Insulation, corona effect, transient)
Rotor	*Stress thermal*
	Stress electromagnetic
	Stress residual
	Stress dynamic
	Stress mechanical
	Stress Environmental

Table II.2 - Classification of source faults with reference to their location: stator or rotor.

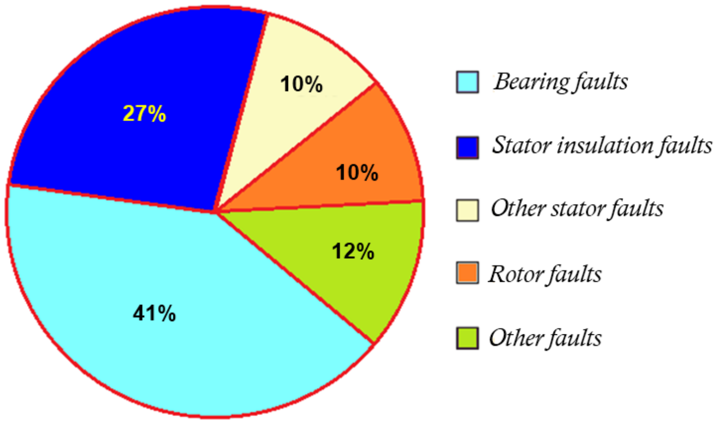


Figure II.20 - Fault rates in the IM (Çalis et al., 2013).

B - Fault Monitoring of Equipment

Machine monitoring play an important and essential role in industrial production. Therefore, it is necessary and highly desirable to monitor and *detect equipment faults* properly, as early as possible before they become inoperable, and to improve availability and reliability. The machine parameters (*current*, *voltage*, *winding temperatures*, *etc*.) should be monitored in accordance with manufacturer's recommendations, industry standards and practices, and plant. Rotating machines *CM* and their *FDi* are essential and can be economically justified *(Singh et al., 2016a)*. *CM* plays a very important role in the production security and the product quality. The demand for *FDe* and *FDi* of rotating machines has increased the efforts to develop new analysis techniques *(Bendjama et al., 2014)*. *CM* have been studied in the recent decade to prevent costly interruptions due to motor faults and recognize faulty conditions as soon as possible *(Li, He, 2012; Devaney, Eren, 2004)*.

CM of machines is the process of monitoring various operating parameters of a machine or set of machines to identify changes which may be indicative of a developing fault. *CM* provides a way to ensure equipment reliability in addition to continuous inspections *(Ronny, 2017)*.

The main *advantage* of this *OLM* is that a *machine* must not be taken out of service. As a result, the normal operation condition can be evaluated while the motor is running. Also *predictive maintenance* is easier because the machine is under constant surveillance so an incipient failure can be detected immediately and actions can be programmed to avoid larger process downtimes. Furthermore, *OLM* allows maintenance to be scheduled, and can significantly reduce maintenance costs and the risk of unexpected failures to allow early detection to avoid unwanted breakdowns, downtime and other consequences of potentially catastrophic damage. Also, *OLM* can increase the lifetime of machines when the faults are diagnosed at the right time *(Goutam, Sathish, 2018).* Hence, *CM* of machines is very important factors in saving cost and energy conservation in industries *(Prainetr et al., 2017).* A disadvantage is that *OLM* techniques often require installation of additional equipment which must be installed on each machine. Compared to *off-line tests,* the *on-line tests* exhibit more difficulty or even impossible to detect some failures in processes *(Hurtado et al., 2015).*

C - Fault Monitoring Methods

To determine the conditions of each part of motor, various testing and monitoring methods have been developed *(Mortazavizadeh, Mousavi, 2014; Glowacz, 2019).* In the literature, *FDi* methods have been developed for the *FDe* and *FDi* of a *DC motor (Abed et al., 2014; Glowacz, 2016a), IM (Singh et al., 2015; Glowacz et al., 2017)* and *synchronous motor (Foo, et al., 2013).* Various monitoring techniques have been developed, such as dynamics, industrial noise and vibration, tribology and non-destructive techniques of structures and rotating machinery. *(Hurtado et al., 2015)* Gave different methods to test and monitor of failures to *IM* to obtained a comparison of advantages and disadvantages for all *FDi*. *(Kia et al., 2012)* aims to provide a comparative study of vibration, acoustic pressure and stator current analysis capabilities for a gear tooth wear *FDi*. Descriptions of *FDi* techniques of machines can be found in the recent literature *(Krolczyk et al., 2014; Li et al., 2016; Lopez-Perez, Antonino-Daviu, 2017)*.

Techniques of monitoring of electrical machines are classified in several manners such as *On-line/ off-line; Invasive and non-invasive; and Electrical, Mechanical, Chemical, Thermal, etc.* Furthermore, these techniques can be *classified* into *time domain*, *frequency domain*, *time-frequency domain (Tandon, Choudhury, 1999), NN (Simsir et al., 2016)* and *MBTs (Jalan, Mohanty, 2009)*.

Related works and literature reviews about fault and *CM* of any machineries were classified into *two categories*: *off-line* and *OLM* through a proper data acquisition and efficient *signal processing* (*SP*) unit *(Kumar, Kumar, 2014; Irfan et al., 2017; Prainetr et al., 2017). off-line methods* are typically more direct and accurate. The user does not need to be an expert in *machinery* but only have basic knowledge for testing. *(Bellini et al., 2008)* discussed the use of *on-line current* and *voltage* based advance *FDi* technique and off-line *partial discharge* test to diagnose winding fault. *Partial discharge* test is an off-line test that requires motor shutdown which can leads to production loss.

The detection techniques of electrical machine failures can be classified in *invasive* or *destructive* and *non-invasive* or *non-destructive* techniques *(Aroui et al., 2007; Merizalde et al., 2017; Irfan, 2019).*

Non-invasive methods allow to surpass the invasive methods. They are the most preferable one because they are simple, precise and economical to detect and diagnose a variety of failure without disintegrating electrical machines, stopping operations, or putting people at risk. As well, these are suitable for *OLM* of the machine. More useful formation is obtained from the stator current, vibration, magnetic field temperature and noise signal. The *non-invasive techniques* involved in mathematical analysis of these signals, to find out the failure of the electric motor.

etc. There are several indicators or signatures for faulty conditions of rotating electrical machines help us to distinguish machine conditions. After fault signature is obtained, it can be used for *FDi*, either by experienced engineer/technician or using some of techniques from the field of *AI*.

For the purpose of *CM* of *electrical machines*, many methods have been developed and may involve several different types of fields of science and technology. The most applied techniques of *CM* that are widely practiced with electrical machines are those involving *Machine Vibration Analysis* (*MVA*) *(Kumar, Kumar, 2014)*,

Motor Current Signal Analysis

Motor-Current Signature Analysis (*MCSA*) (Bień, Duda, 2011), thermal and *IRT* (Eftekhari et al., 2013; Singh et al., 2016b), *analysis of ultrasonic and acoustic signals* (Kia et al., 2012; Glowacz, 2015; Li, Li, 1995; Glowacz, 2019), *analysis of magnetic field or flux signals* (Constantin et al., 2013; Fireteanu, 2013) and *lubrication analysis* (Kessissoglou, Peng, 2003).

These techniques have been commonly used as an effective tool for detecting various machinery faults in several researches and all of them are attempting to offer a reliable *FDi* to protect the machine life and to ensure the profit of both manufacturers and customers.

In an *ISO* working party, it was identified that the main techniques for machine monitoring are: *vibration measurements*, *electrical measurements*, *process and performance* measurement and *non-destructive* testing (Yang Hongyu, 2004).

The selection of the *FDi* signal and the method of searching for symptoms of damage related to the *SP* algorithm used, have a direct impact on the speed of the detection process.*CM methods* for machinery can be analyzed in *four main groups*: *electrical* and *magnetic*, *mechanical*, *chemical* and *thermal* behavior of the motor under steady-state and fault conditions as it is illustrated by *Figure II.21* (Merizalde et al., 2017). In each group, there are several symptoms that faulty condition in machines can be detected by them. (*a*) First, *electrical methods* are based on *electrical symptoms* like *current signature*, *voltage*, *flux*, *power* and so on. In most cases, fault is detected by comparison between electrical signals in healthy and unknown conditions. (*b*) The most common *mechanical methods* are based on *mechanical symptoms* like *torque*, *vibration* and so on. (*c*) *Chemical indicators* are assigned to some chemical parameters of materials *like oil characteristic* or *wear* and *debris* in *oil analysis*. (*d*) In last group, *thermal methods* for rotating electrical machines has the aspect of measuring the temperature (Mortazavizadeh, Mousavi, 2014).

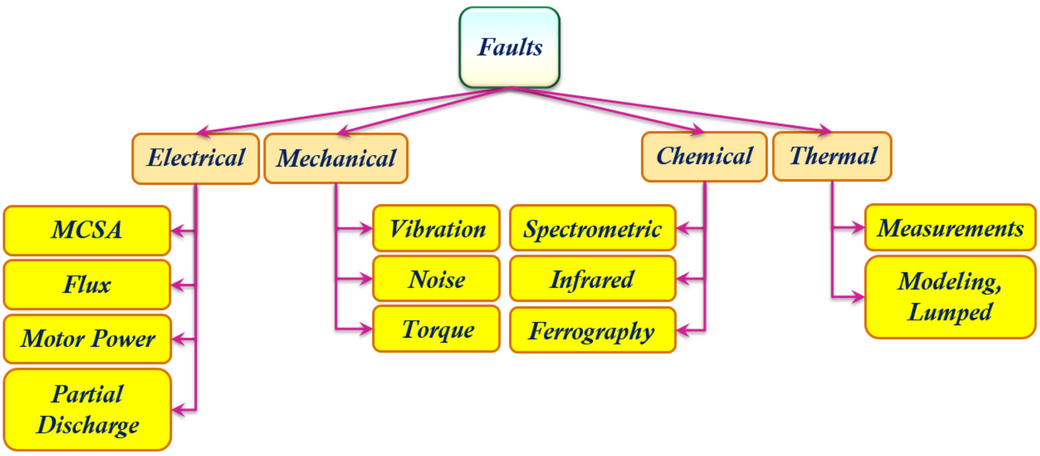


Figure II.21 - Classification of FM methods (Mortazavizadeh, Mousavi, 2014).

Figure II.22 shows a block diagram of the general approach about *on-line CM*. Starting from the left, common *Machine faults* are shown.

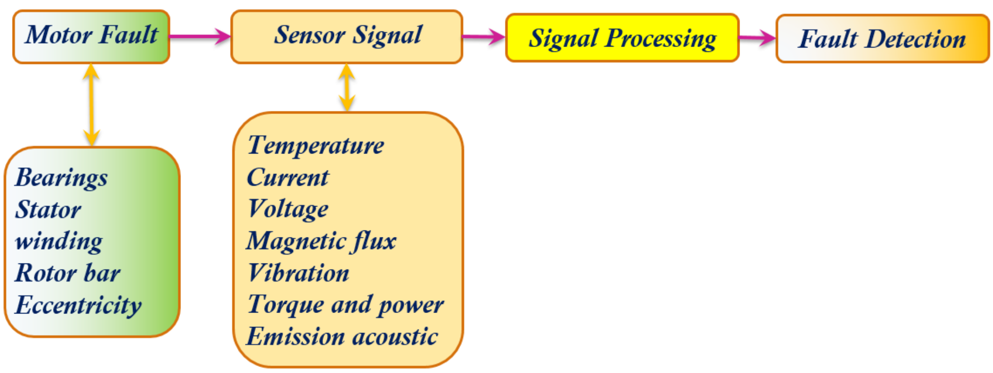


Figure II.22 - General approach of on-line CM (Hurtado et al., 2015).

The next block show different types of sensors can be used to measure signals to detect these faults. All *FDe* techniques require prior knowledge of the machine behavior by measuring the appropriate data in order to distinguish normal operation conditions from failure conditions. Various *SP* techniques can be applied to these sensor signals to extract particular features which are sensitive to the presence of faults. Finally, in the *FDe* stage, a decision needs to be made as to whether a fault exists or not (*Hurtado et al., 2015).*

C1 - Electrical Analysis

Most popular of the *Electrical Signature Analysis* (*ESA*) for *CM* of electrical machines are: *MCSA (Kalaskar, Gond, 2014), Voltage Signature Analysis* (*VSA*), *Extended Park's Vector Approach* (*EPVA*) and *Instantaneous Power Signature Analysis* (*IPSA*) *(Kucuker, Bayrak, 2013)*. *ESA* also includes *Motor Circuit Analysis* (*MCA*) *(Penrose, 2008)* involving *analysis of resistance*, *impedance*, *inductance*, *phase angle*, *current/frequency response* and *insulation to ground faults*. Other methods can be found in literature such as *leakage currents*, *high frequency impedance/turn to turn capacitance, motor power monitoring* and *partial discharge monitoring. Leakage currents* are a non-invasive monitoring method based up on measurement of the differential leakage of currents through the ground conductor *(Gubric et al., 2008)*. This method is useful to find out the condition of the insulation system allowing the calculation of an equivalent capacitance between phase to ground and phase to phase as well as a dissipation factor.

A non-invasive monitoring system using *high-frequency response* of the motor is presented by *(Gubric et al., 2008*; *Grubic et al., 2008; Stone et al., 2014).* This system is capable of perceiving the deterioration of turn-to-turn insulation by detecting small changes in capacitance between each turn of stator winding. This method shows that when the turn to turn capacitance of the stator winding changes, the impedance spectrum also changes. To determine the status of insulation, the impedance response is compared to a response recorded after that the motor has been manufactured or the dissipated power through insulation is calculated and compared against a target value, which can be determined by historical data of similar motors *(Hurtado et al., 2015).*

Motor *Power Signature Analysis* (*PSA)* is focused on the detection of double-slip frequencies present in the electric input power spectrum *(Legowski et al., 1996)* similar to *MCSA*. These harmonics are evaluated with respect to the average power (*DC* component), thus obtaining some fault severity factors. In addition, this method needs to acquire both currents and voltages. Also the dependence on the drive inertia is another limitation of this fault indicator. *(Bellini et al., 2001)* tried to detect rotor broken bar by using motor *PSA* technique. *(Bień, Duda, 2011)* presented a technique, based on the *TFA* of the current supplying the motor, for estimating speed and slip of the *IM* from the fluctuation of amplitude of the main current harmonic.

By using *Partial Discharge Analyzer* (*PDA*), sensors placed within the winding or at the winding terminals, stator winding *partial discharge* pulses will separate from electrical interference (usually harmless) based on pulse arrival time or pulse shape and easily can be detected *(Stone et al., 1997). Partial discharge* is a symptom of many stator winding insulation failure mechanisms. *(IEEE, 1434-2000)* reviews all types of *partial discharge* measurement methods used in rotating machines. *(Bellini et al., 2008)* discussed the use of *on-line current* and *voltage* based advance *FDi* technique and *off-line partial discharge* test to diagnose winding fault. *Partial discharge* test is an *off-line* test that requires motor shutdown which can leads to production loss.

a - MCSA or Current Spectral Analysis.

Stator current is the signal most often used in the *FDi* of winding failures, mainly due to the measurement simplicity *(Skowron et al., 2019b).* Concept of *MCSA* originates from early 1970s and was first proposed for use in *NPPs* for inaccessible motors and motors placed in hazardous areas *(Korde, 2002)*. *MCSA (Thomson, Gilmore, 2003)* is an interesting *non-invasive monitoring* technique, rapidly gaining acceptance in industry today and have high recognition efficiency. *MCSA* is a method from wider field of *ESA (Salomon et al., 2016)*, useful for identify failures not only in *electrical machines*, but also in *generators*, *power transformers* as well as in other *electric equipment*. *MCSA* is the technique used to analyze and monitor the trend of dynamic energized systems. *MCSA* is monitoring stator current (more precisely supply current) of the motor. In ideal case, motor current should be pure sinusoidal wave. In reality in motor current many harmonics are present. Developing motor faults have its counterparts in waveform and harmonic content of the motor supply current. In operation, motor fault modifies harmonic content of the supply. Single stator current monitoring system is commonly used (monitoring only one of the three phases of the motor supply current) (*Figure II.23*) *(Miljkovic, 2015).*

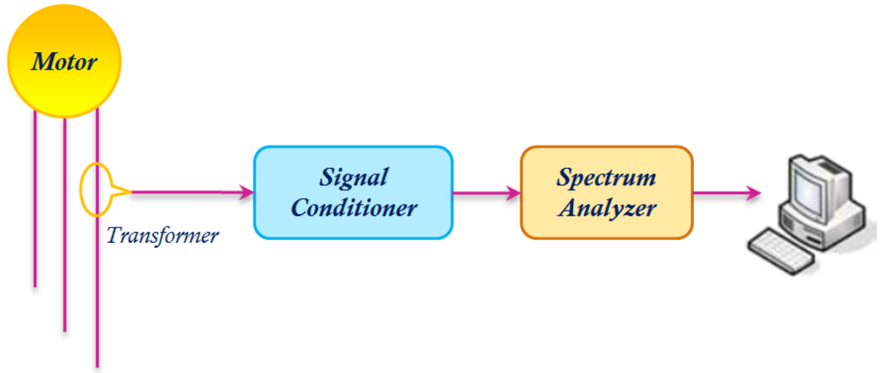


Figure II.23 - Stator current monitoring system.

Various *mechanical* and *electrical faults* can cause anomalies in the spectrum of stator current. If a *short circuit* occurs on some stator windings, either between windings or turns of the same phase or between different phase windings, the configuration of the rotating magneto-motive force is affected. As a consequence, harmonic components of the stator currents will also be affected on their amplitudes.
On the other side, the amplitude variation of harmonic components is affected not only by the fault but also by the load on the motor. So it is convenient to perform comparisons under similar loads.
By analyzing the spectrum of the motor current, *MCSA* has become an important *FDi* tool for detecting *IM faults* such as *broken rotator bar*, *bearing damage*, *misalignment*, and *air gap eccentricity* *(Benbouzid, 2000; Ye et al., 2003)*.

In the literature, *FDi* techniques based on the analysis of *defect signatures* in *electric currents* were developed *(Szabó et al., 2008; Mousavi M. et al., 2017).* In *(Szabó et al., 2008)* have been compared different *FDi* methods like three phase current vector, the instantaneous torque, and the outer magnetic field. Finally, it's declared that *MCSA* can be the best method for diagnosis the rotor faults. *(Mousavi M. et al., 2017)* investigated and detected faults under variable loading and speed conditions by studying the *MCSA* using a novel developed parallel technique based on the *Discrete Wavelet Transform* (*DWT*).

MCSA can be applied everywhere in industry where *IM*s are used enabling non-intrusive analysis of motor supply current. *MCSA* has high recognition efficiency and is one of the most popular approaches since are performed on-line without interrupting production with motor running under the load at *NOCs* *(Korde, 2002)*. It has been proven that *MCSA* provides the information to diagnose accurately diverse fault in stator and bearings and it is a way for *FDe* in *permanent magnet motor* for an elevator application *(Royo et al., 2008). MCSA* can be used as predictive maintenance tool for detecting common motor faults at early stage. Furthermore, *MCSA* provides sensorless diagnosis of rotor and bearing problems and an electric signal is easy to process, because it is not so mixed together. Therefore, the use of *MCSA* prevent expensive catastrophic failures, production outages and extend motor lifetime. However, recognition of motor current fault signatures requires from user considerable degree of expertise and experience. *MCSA* constitutes a complement and powerful addition for *FDi* to *MVA* *(Çalış, 2014; da Gama et al., 2017)* and *thermal monitoring. MVA* has an inherent limitations in detecting earlier electrical problems such as *air-gap eccentricity*, *short circuits on stator winding's turn to turn* or *rotor broken bars* *(Hurtado et al., 2015)*.

However, its advantages, *MCSA* present some drawbacks. it's not so effective for applications where the load constantly changes *(Mortazavizadeh, Mousavi, 2014).* The prior *MCSA* techniques assume *stationary* and *high SNR* for signal. The nonstationary of stator current is accommodated by the commonly used *windowing techniques (Gupta et al., 2011)*. Furthermore, *current signal* can be used only for limited faulty states such as: *shorted windings*, *broken bars*, *faulty ring of squirrel-cage (Antonino-Daviu et al., 2015; Yang et al., 2016)*. Access to the electric signal is not so easy (comparing with acoustic signals). Because of the proximity of main signal frequency to produce components and sidebands, broken bar detection may be difficult by *MCSA* method *(Wang, 2008)*.

C2 - Mechanical Analysis

There are *several mechanical symptoms* for faulty condition of electrical machine, such as: *vibration*, *acoustic noise*, *torque* and so on. *Vibration and acoustic noise* occurs due to rotor eccentricity which may involve many different factors, including: *fluctuation in loads*; *damaged bearings*; *broken rotor bar* and *improper mounting* of the machine *(Kim et al., 2014)*. When a failure begins to occur on a machine, vibration and levels of emission acoustic increase *(Siddique et al., 2005; Gubric et al., 2008; Verucchi et al., 2008)*.

A severe mechanical problem in any component influences necessarily the electric machine through load and shaft speed. Bearing faults can introduce particular eccentricities and load *torque* oscillations. These oscillations can be caused by load unbalance, shaft misalignment, a broken ball in a bearing and gearbox fault *(Blödt et al., 2010). (Blödt et al., 2006)* have examined the detection of mechanical fault-related load *torque* oscillations in *IM*s using a stator current monitoring. The *torque* estimation is done using multiple regression method by extracting the energy possessed in the processed acoustic signal and the faults are diagnosed precisely *(Sangeetha, Hemamalini, 2019).*

a - Mechanical Vibration Analysis

Vibration signals carry a great amount of information about the equipment condition**.** Techniques based on the *vibration analysis* are considered as vital and very common used to detect anomalies *(Scheffer, Girdhar, 2004; Han, Song, 2003)* in electrical machines. *Vibration monitoring* has been used routinely in *NPs*. For example, bearing faults in a reactor coolant pump can lead to high vibration that can cause a reactor trip. Therefore, vibration monitoring provides a way to monitor the equipment in *NP (Reimche et al., 2003).*

Vibrations on an *equipment* appear as a result of periodic forces acting between the moving parts (*Hurtado et al., 2015).* The vibration signal is the oscillatory response of a mechanical system that may be representative of its free and natural dynamic behavior which can be excited by external sources. This behavior will be changed in case of any kind of mechanical abnormality in the electromechanical system *(Kia et al., 2012).* Vibration signal is characterized by (*a*) *amplitude* which helps in detecting the severity of the fault condition or failure; (*b*) *frequency* which helps in indicating the cause of the failure; and (*c*) *phase* which helps in determining the cause of the fault. *Vibration amplitude* can be measured in terms of *displacement*, *velocity*, *acceleration*. Phase indicates how a machine is moving to a reference of its part *(Goutam, Sathish, 2018).*

Vibration signal analysis is used in a general way for *FDi* of mechanical part of an equipment. In many cases, the overall vibration level of the machine is sufficient to diagnose mechanical failures *(Tavner et al., 2008),* but in some cases this is not an efficient method *(Mortazavizadeh et al., 2012; Mortazavizadeh, Mousavi, 2014).*

There are *many mechanical* problems associated with *vibrations* and common problems are: unbalance of rotating parts, eccentric components, misalignment, bent shafts, component looseness, damaged gears, worn drive belts and defective bearings *(Rao, 1996)*. The vibrations of a gear are mainly produced by the shock between the teeth of the two wheels. Meanwhile, vibration causes periodic constraints in machine parts, which lead to fatigue, wear or damage *(Yang Hongyu, 2004)*. Any machine faults are accompanying by abnormal vibrations (amplitudes and/or frequencies). If a machine is well designed, and without failure, the vibration response should be reduced. When the failure begins to occur, the dynamic forces operating on the machine varies, and consequently its vibrational response also varies *(Hurtado et al., 2015).* Therefore, the vibration level is a significant parameter carrying information characterizing the operating state of some mechanical parts of the machine. The increase of these vibration is an indicative of the degradation state of machines *(Bendjama et al., 2014).* Therefore, a motor considered as an electro mechanical device, its mechanical faults is easily detectable by vibration *(Tulluri et al., 2015; Collacott, 2012)*.

MVA can be classified into two types: *deterministic* and *random*. The *deterministic* vibrations produce a cyclic vibration response and they can be defined by mathematical equations expressing the evolution over time. On the other hand, *random vibrations* can only be analyzed by statistical means. (*Hurtado et al., 2015).*

Many articles described techniques based on *vibration analysis* are used to detect and diagnose faults *(Kumar, Kumar, 2014; Sadeghi et al., 2017; Goutam, Sathish, 2018)*. *(Bendjama et al., 2014)* have used the vibration measurements for *FId* in rotating machinery. *(Dorrell et al., 1997)* illustrated how eccentricity faults can be identified from *vibration analysis* using *CM* techniques. *(Pöyhönen et al., 2003)* showed that the electromagnetic force is the most sensitive indicator of air gap eccentricity. Therefore, identifiable signatures should be found in the *vibration pattern* of rotating electrical machines. The only drawback of this indicator is its low accessibility.

Many techniques have been reported for *FDi* based on vibration signals, and they aim at finding some efficient fault features from the vibration signals *(Kumar, Kumar, 2014).* With the rapid development of *SP* techniques, it has become possible to extract useful information from vibration data *(Bendjama et al., 2014).* The first possible observation of a vibration signal is the temporal representation *(Bendjama et al., 2014).* Temporal representation of the vibration signal defines several indicators, such as *peak value*, *peak to peak value*, *root mean square value*, *kurtosis*, and *crest factor (Tandon, Choudhury, 1999)*. Features in time domain, such as *standard deviation* of vibration signals are also frequently used for vibration monitoring *(Reimche et al., 2003)*. *Spectral Analysis* (*SA*) *of vibration signals* is a common tool for *vibration monitoring*. It allows to identify the different frequencies of the original signal. The spectrum of a vibration signal can be trended and compared with fault-free baseline measurements to detect any developing faults *(Reimche et al., 2003).*

The spectrum of the vibration signal is usually given in sampling time. When a nonstationary signal is transformed into the frequency domain, most of the information about the transient components of the signal will be lost *(Douglas et al., 2005)*, hence, a time-frequency methods has been proposed in *(Lebaroud, Clerc, 2008)*. In the field of machinery *FM*, *time-frequency methods* are mostly used in *MVA* and *MCSA (Mortazavizadeh, Mousavi, 2014).* There are several *TFA* methods, such as the *Short-Time Fourier Transform* (*STFT*), *Wavelet Analysis* (*WA*), and the *Wigner-Ville Distribution* (*WVD*), which may be used for *CM* of rotating machinery in transient and unsteady operating conditions. Those time-frequency techniques have been applied to *FDi* and *CM* in practical plant machinery *(Purushotham et al. 2005; Wu, Liu, 2008)*. Also *Hilbert transform* and *Zhao–Atlas–Marks distribution* in *(Rajagopalan et al., 2006)* applied to *FDi* of motors in nonstationary conditions but this method is not as common as prior methods. *WA* has been used widely in the *FDi* of rolling bearings, gearbox and compressors. This technique also has been used for feature extraction and noise cancellation of the various signals *(Purushotham et al. 2005)*.

Similarly to the *analysis of electric currents*, methods based on the vibration analysis have high recognition efficiency. Advantages *FDi* techniques based on vibration are inexpensive vibration sensor, immediate measurement of the vibration signal, it is possible to analyze electrical and mechanical faults *etc.*, and easy access to vibration signal. Indeed, *vibration analysis* is generally capable of detecting more kinds of faults compared to other techniques. It also has advantages as a non-destructive, clean, relatively simple and cost-effective technique. In spite of wide use of vibration measurement for *FDi* of different types of machinery faults, the *drawbacks* of *vibration analysis (Wang et al., 2016a)* are the error in measurement due to improper mounting of sensors because they should be very close to the motor *(Prainetr et al., 2017).* Furthermore, sometimes, the vibration measurements, which represent in fact some parts of the machine, are difficult to read due to the nature of the vibration signal and background noise due to external excitation motion, inaccessibility in mounting the vibration transducer and the sensitivity to the installation position *(Mohanty, Kar, 2006; Bendjama et al., 2014).*

b - Acoustic Emissions

The most of rotating electrical machines generate acoustic noise signals *(Glowacz, 2016a).* Measuring and *analyzing the acoustic noise spectrum (Metwalley, Abouel-seoud, 2013)* is another method of *CM* in rotating electrical machines. *AE* is the elastic energy released by materials when they undergo deformation *(JSNDI, 2016).* This rapid energy release causes stress waves that radiate from the source and are detected and monitored by sensors placed on material surfaces. *AE* anlysisis a non-destructive testing technique used to monitor rotating machinery vibration. Acoustic emission-based *CM* was described in the article *(Caesarendra et al., 2016)*. The *American Society for Testing and Materials* (*ASTM*) defines *AE* as "the class of phenomena whereby transient stress/displacement waves are generated by the rapid release of energy from localized sources within a material, or the transient waves so generated" *(ASTM, 2011)*. For a fault that has occurred in an machine, the acquired acoustic signals have both oscillatory and non-oscillatory components and are distinct for different faults in rotating machines *(Sangeetha, Hemamalini, 2019).*

Acoustic analysis has gained interest in *CM* and *FDi* in the recent past. The acoustic emission is used for *FDe* as *single phasing*, *bearing cage damage* and *broken rotor bars (Sangeetha, Hemamalini, 2019).*

For example, defects in the roller element bearings cause particular frequencies that can be detected in acoustic noise spectrum. Acoustic noise emitted from air gap can be an indicator of probably eccentricity in *IM (Mortazavizadeh, Mousavi, 2014).*

The fault components in the processed *acoustic signal* changes with both *amplitude* and *time* in an unpredictable way. When the oscillations in signals are small, frequency domain method like Fourier analysis can be applied, compromising the accuracy in *FDi*. However, for accurate analysis and to identify the fault related frequency components the acoustic signals should be analyzed in time-frequency domain *(Sangeetha, Hemamalini, 2019).*

(Baydar, Ball, 2001) examined whether acoustic signal can be used effectively to detect the various local faults in gearboxes using the smoothed *Pseudo Winger-Ville Distribution* (*PWVD*). In *(Scanlon et al., 2007)*, an automated approach to degradation analysis is proposed that uses the acoustic noise signal from a rotating machine to determine the remaining useful life of the machines. In *(Glowacz, 2016a),* the author presented a technique of recognition of acoustic signals of the *DC motor*. *(Glowacz et al., 2017)* described an early *FDi* technique of *single-phase IM* based on *acoustic signals*. The authors measured and analyzed following states of the motor: healthy single-phase *IM*, *single-phase IM* with faulty bearing, *single-phase IM* with faulty bearing and shorted coils of auxiliary winding.

(Prainetr et al., 2017) presented a description of bearing, stator and rotor *FDi* methods of a *single-phase IM* by using *acoustic signals*. *FDi* of stator faults of the *single-phase IM* using acoustic signals was presented *(Glowacz A, Glowacz Z, 2016)*. In *(Sangeetha, Hemamalini, 2019)*, *FDe* in a *three-phase IM* is done by estimating the torque from the *acoustic signals* released by the machine. *FDi* of acoustic signals of loaded synchronous motor was also described *(Glowacz, 2016b)*. Automatic bearing *Fault Localization* (*FLo*) using vibration and acoustic signals was analyzed in the literature *(Jena, Panigrahi, 2015)*. Analysis of acoustic emission signal for bearing fault was also presented *(Wang et al., 2016b)*.

There are some *advantages* of *AE* such as easy access to acoustic signal, inexpensive microphone, possibility to analyze electrical and mechanical faults (shorted windings, broken bars, bearings, rotor shaft, *etc.*) *(Islam et al., 2016; Stief et al., 2017)*. Furthermore, measurement of acoustic signals is immediate and non-invasive.

However, the *CM* based on acoustic pressure measurement has received less attention probably due to industrial environments embedded noise in the acoustic signal. The application of the acoustic measurement in a noisy environment like a plant is not so efficient *(Mortazavizadeh, Mousavi, 2014).* Another disadvantage of acoustic based *FDi* techniques is the lack of changes in the acoustic signal for some types of electrical equipment *(Glowacz, 2019).*

C3 - Thermal Analysis

The temperature rise in *IM* can be due to the failure of cooling system. Indeed, a blockage or failure of the cooling system stops forced convection and generates excessive heat which ultimately reduces motor efficiency and leads to increase in the motor surface temperature, increases stator temperature, and can lead to failure of winding insulation. As a rule that states, with every 10°C rise in temperature leads to reduction of insulation life to half *(Rangarajan et al., 2007)*. In addition, inter turn fault leads to increase in motor stator temperature due to over current. The failure of cooling system commonly arises due to accumulation of dirt, blockage of air passage, damage or loose rad fan and improper clearance while installation*(IEEE, 2007)*. Therefore, it is essential to monitor *machine temperature* and cooling system blockage or failure along the time by using appropriate methods at earlier stages before a major breakdown may occur *(Gubric et al., 2008)*. Indeed, *cooling of IM* improves the life of winding insulation. Thermal images are very useful in detecting incipient fault and also deterioration in *IM*s caused by overheating in stator windings *(Eftekhari et al., 2013).* Furthermore, *vibration* and *current monitoring* based techniques are found to be *not suitable* for monitoring and *FDi* of *cooling system failure* of *IM (Singh et al., 2016a).*

There are *three main approaches* for *temperature measurement* in electrical machines: (*a*) Measuring local point temperatures by *Embedded Temperature Detectors* (*ETDs*) or *RTD*; (*b*) Using *analysis of thermal images* to monitor the temperature of the perceived hottest spot in the machine; (*c*) Measuring distributed temperatures of the machine or bulk temperatures of the coolant fluid *(Tavner, 2008)*. Furthermore, temperature can be monitored internally of the motor by integration of temperature sensors within the stator, the stator core, the frame, or even might be part of the cooling system. Different types of temperature sensors such as *RTD* or *thermocouple detectors* can be used. These procedures can be used by maintenance personnel in many machines to draw conclusions about the *coolant* and *current condition of insulation,* and the machine shuts down if it exceeds a certain temperature *(Siddique et al., 2005; Gubric et al., 2008)*.

(Singh et al., 2016a) showed that failure of the cooling system not only leads to rise of the motor stator temperature but also increases the fan cowing surface temperature. *(Garcia-Ramirez et al., 2014)* presented a methodology based on *thermographic* image segmentation for detecting broken bar, bearing, misalignment, mechanical and voltage unbalance faults in *IM*s, and the repercussion of these faults along the kinematic channel. *(Manana et al., 2011)* described a simplified thermal model besides *thermal images* for *FDi* of *open winding fault* in *DC motors*, during manufacturing. In *(Barrera et al., 2009) thermal images* are used for *FDi* of *stator core fault* in *IMs*. *(Younus, Yang, 2010; Younus et al., 2010),* used *thermal images* for *FDi* of different faulty conditions such as *misalignment*, *mass-unbalance* and *bearing-fault*.

The rise in the motor surface temperature can be detected and diagnosed by *thermographic* inspection and some literatures addressed this issue *(Picazo-Rodenas et al., 2014). IRT* is defined as an acquisition surface temperature pattern by scanning the *Infrared (IR)* emissions from the surface using thermal imaging devices in *ISO* standard. *IRT* is an on-line and non-contact type *CM* technique *(Rangarajan et al., 2007)*, which has been used widely for inspection of electrical equipment and transformers. Therefore, *IRT* is *non-invasive* inspection technology which makes it a valuable tool to assist *FDi*. Improvements in *IR* technology by new generation of

IRT cameras and better capability of image processing algorithms have led to great strides in practical applications. *IRT cameras* detect radiation in the *IR* range of the electromagnetic spectrum and produce images of these radiations. The amount of *IR* radiation emitted by an object increases with temperature; therefore, thermography allows one to see temperature profile. As a result, in health monitoring motors, the amount of radiation on the surface of motor body can reflect its operating condition and inside thermal condition *(Eftekhari et al., 2013).*

(Singh et al., 2016b) proposed an on-line and non-invasive technique that uses *IRT*, in order to detect the presence of *inter-turn* fault in *IM* drive. *(Manana et al., 2011)* proposed a *thermal model* and an *IR* monitoring test method for field winding *FDe* during manufacturing of *DC machines*. In *(Eftekhari et al., 2013),* an algorithm based on the features extracted from *IR images* taken from the hottest region of the motor surface, is proposed to detect *inter-turn short circuit faults* in the *stator windings* of an *IM*. *(Singh et al., 2016a)* have focused on monitoring of *thermal changes* of these two regions in *IM* by using *IRT* technique under load and no load operating condition, which helps in detecting the failure of the cooling system at early stages of blockage. *(Widodo et al., 2011)* implemented self-organizing map for machine *FDi* such as outer and inner race defects of rolling element bearing, unbalance, misalignment and looseness based on *IR images*. In *(Eftekhari et al., 2013),* the authors proposed a novel expert algorithm based on *IRT* for on-line diagnosing of *inter-turn short circuit fault* in stator windings of *IMs*. *(Singh et al., 2016b)* proposed an algorithm for automatic inter turn *FDe* in *IM*s and to estimate its severity level based on its *IRT* images.

Thermal monitoring of cooling system failure of *IM* is found to be very effective *(Singh et al., 2016a)* and the analysis of thermal images is also very efficient for *FDe (Prainetr et al., 2017).* However temperature estimation based on *thermal model* is flexible and accurate, but it can't respond to the changes in motor thermal characteristics *(Rangarajan et al., 2007)*. Furthermore, the effectiveness of thermographic techniques for *FId* in *IM*s is highly dependent on its accuracy in identifying the hot areas and predicting its severity level *(Singh et al., 2016b).* In addition, there are some other drawback such as expensive thermal imaging camera, it takes time to heat up motor, it takes time to process thermal images *(Glowacz, 2019).* Although, there have been some new efforts in using *IR images* for *FDi* of machine faults, thermal images have not received wide application on rotating electrical machines *(Eftekhari et al., 2013).*

C4 - Electromagnetic field

Magnetic flux can be a fault indicator and monitored both *inside* the machine or *outside (Mortazavizadeh, Mousavi, 2014)*. This method is *non-invasive* and simple measurement and low cost of sensors.

The *external stray flux signal* results from changes in the electromagnetic field of the machine due to asymmetries related to motor defects *(Henao et al., 2003; Ceban et al., 2012)*. Methods based on the analysis of *external magnetic fields* have been developed for *bearing (Frosini et al., 2015), stator winding (Surya et al., 2017), rotor broken bars* and *eccentricity fault (Ebrahimi, Faiz, 2010)* in *induction machines*. The detection of the short-circuit fault in the stator winding based on the evaluation of the harmonics of the *magnetic field outside the motor* represents a simple and efficient solution. A better efficiency of the *FDe* is obtained if the magnetic core of the motor is characterized by a lower magnetic saturation *(Constantin et al., 2013).* Furthermore, the use of an *axial flux* in the *FDi* of electrical machines is discussed in *(Ewert, 2017)*.

However, the drawback of the analysis of external magnetic fields is the difficulty in modeling the magnetic field, which is strongly depends on the electromagnetic behavior of the stator *(Sangeetha, Hemamalini, 2019).* On the other hand, *coil installation* and *noisy spectra* are the main *difficulties (Bruzzese, 2008)*.

(Dorrell et al., 1997) showed a relation between air *gap eccentricity*, *air gap flux* and *vibration signals*. *(Cruz et al., 2008)* presented a *FDi* algorithm of rotor faults by using the measurement of the amplitude of the *rotor flux oscillations*. *(Fireteanu, 2013)* studied the signature of the short-circuit faults inside the stator winding in the

magnetic field outside IMs based on the time domain finite element analysis of the electromagnetic field. The detection of such a fault is based on the evaluation of the output voltage of coil sensors placed in the motors neighboring and the comparison of amplitudes of harmonics of this voltage for the healthy and faulty operation states.

C5 - Chemical

Stator winding insulation degradation can be monitored chemically by the presence of special matter in the coolant gas or by detection some particular gases such as *ozone*, *carbon monoxide* or even more complex *hydrocarbons*, like *acetylene* and *ethylene* *(Tavner, 2008)*. Electrical discharge activity, heat and some other electrical and mechanical faults may lead to *insulation degradation* *(Mortazavizadeh, Mousavi, 2014).* In addition, oil particle can be used for *FDi*. Some types of oil analyses are: viscosity, solids content, water content, total acid number, total base number and flash point *(Scheffer, Girdhar, 2004)*.
The monitoring of machine conditions Can also be done with *tagging-compounds.* These monitors can be described as "*smoke detectors*", *(Gubric et al., 2008*; *Stone et al., 2014). Tagging-compounds* are paints that emit particles with unique chemical properties at high temperatures. These particles can be easily detected by monitoring, indicating if a certain temperature is reached by the motor. Basically these unique particles appear and are detected when the winding is at very high temperature and insulation system is close to failure (*Hurtado et al., 2015).*

D - Industrial Systems

Today various expert systems, automatic *FDi* and analysis systems have been developed to aid and simplify the *FDi* process. One such system is *Electric Motor Performance Analysis & Trending Hardware* (*EMPATH*) developed by *Framatome ANP (Waarli, 2010). AnomAlert Motor Anomaly Detector* is a system of software and networked hardware that continuously identifies faults on electric motors and their driven equipment *(Swift, 2012).* System possess learning ability and alarming function based on statistical analysis. It does not for the most part provide precision *FDi* of particular fault but reports indication of particular categories of faults for closer inspection. *ALL-TEST* is a system for troubleshooting equipment using *ESA*. An *ALL-TEST Pro* kit includes *ALLTEST IV PRO 2000* motor circuit analyzer, the *ALL-TEST PRO OL* motor current signature analyzer, *EMCAT* motor management software, Power System Manager software, and *ATPOL MCSA* software, *(Penrose, 2004)*. System for automatic monitoring and *FDi* in *IM*s that can be operated remotely (including web interface) and in real-time is described in *(Terra et al., 2010).* It can trigger alarms whenever a fault is detected including turning off a motor in case of a short-circuit detection.

II.3.4.3 - Power Electronic Monitoring

Power electronics technology has played an indispensable role in the power industry and its applications have been widely used on manipulating the electric energy for power conversion purposes. Nowadays, this technology is widely used in several fields: domestic, commercial and industrial applications such as aerospace, military and nuclear; and its use is still increasing in electric power systems *(Kamel, et al., 2015; Malinowski et al., 2019).* In such applications, a high level of reliability and efficiency is required**.** The continuous operation could be critical and must be insured, despite of failures that may occur in different systems. Furthermore, a variety of motors are widely used for many purposes like pumping (cooling water, fluids, lubricant oil *etc.*) and ventilation.

Hence, Variable speed *AC* motor drives with power electronic converters have been under development for a long time and are now a mature technology. High reliability motor drives are of paramount importance to maintain *NP* functionality despite of failures that may occur in the inverter, motor/generator and control system *(Manoharal., 2017; Malinowski et al., 2019).*

Most of the power electronic devices normally operate in an environment requiring rapid speed variation, frequent stop / starting and constant overloading. The circuits are subject to constant abuse of overcurrent and overvoltage. Although protection devices such as *snubber circuits* are commonly used, switching devices are physically small and thermally fragile *(Khanniche, Mamat-Ibrahim, 2001).* When a fault occurs in a power electronic circuit (*e.g.,* essential components fail), it affects several if not all voltages and currents on nodes and in branches, respectively *(Chen, Bazzi, 2013).*

For the previous raisons, the reliability of the components and devices is an area of great interest for the power electronics community *(Malinowski et al., 2019).* The knowledge and information about the fault behavior of power electronic circuits is important to improve system design, protection and fault tolerant control *(Khanniche, Mamat-Ibrahim, 2001).* Therefore, the need of integration of *FDId* and *Fault Tolerant* (*FTo*) techniques for power electronic systems has inspired extensive research in this area in recent years *(Chen, Bazzi, 2013). (Malinowski et al., 2019).* Unfortunately, *Condition Monitoring* (*CM*) of the power electronic systems only received a little attention compared with *FDi* of motor *(Cameron et al., 1986; Hargis et al., 1988; Penman et al., 1986)*.

The two *components* most prone to failure in *switch-mode drives* are *electrolytic filtering capacitors* and *controllable power semiconductors* or *transistors* such as *Metal Oxide Semiconductor Field Effect Transistors (MOSFETs)* and *Insulated Gate Bipolar Transistors* (*IGBTs*) *(Military Handbook, 1991; Yang et al., 2009, Yang et al., 2010b)*. Two main fault types in *switch-mode drives* are *open-circuit* (*OC*) and *short-circuit* (*SC*) faults. Significant work has been done to diagnose *switch OC* in multiple systems, such as *matrix converter drive systems (Sangshin, Taehyung, 2009; Estima, Cardoso, 2011; Yong et al., 2012)* switch *SC (Ehsan, Norman, 2011)*, and other components including *inductors (Esfandiari, Bin Mariun, 2011; Jordan et al., 2009)*, *capacitors (Sher et al., 2012; Tamer et al., 2012)* and *diodes (Palanichamy, Chinnasamy, 1984)*. *Electrolytic bus capacitors* are the weakest link in *motor drives (Military Handbook, 1991)*. Degradation occurs for various reasons, including thermal stresses, transients, reverse bias, and strong vibrations *(Kulkarni et al., 2009)*. Thermal stress caused by high ambient temperatures and self-heating from ripple currents is the leading cause of premature failure. As a capacitor ages, heat from the environment and internal resistance causes the electrolyte to vaporize and escape through the end seal. This loss of electrolyte causes a corresponding increase in *Equivalent Series Resistance (ESR)*. Because of its central role in the failure process, *ESR* is a reliable indicator of capacitor health *(Kulkarni et al., 2009; (Gasperi, 2005)*. Premature *MOSFET* failures are caused by a number of different phenomena. The two leading causes are thermal stress and gate oxide breakdown. Both of these mechanisms increase the on-state resistance *(Orsagh et al., 2005)*. Giving insight into *converters*, plenty of research has been concentrated on *IGBTs*. Conventional techniques mainly focused on detecting any type of malfunctioning of an *IGBT*. *IGBTs'* degradation phenomenon has been proved and modeled by *(Ginart et al., 2008)* in the application of power drive. The leading causes of *IGBT* failures are similar to those noted above for *MOSFETs*. In *IGBTs*, thermal stress leads to bond-wire failures and higher junction temperatures. As a result, the *Collector-To-Emitter Saturation Voltage* (*CESV)* rises *(Ciappa, Fichtner, 2000).* This increase in *CESV* indicates an impending failure in the *IGBT*.

(Khanniche, Mamat-Ibrahim, 2001) describes a method of detection and identification of *transistor* base drive *Open Circuit* (*OC*) fault of 3-phase *voltage source inverter* (*VSI*), feeding a *FL* controlled induction motor. The detection mechanism is based on a novel technique of *Wavelet Transforms (WT)*. In this method, the stator current is used as an input to the system**.** Several recent works have addressed the *FDe* of different faults in power electronics components. *(Chen, Bazzi, 2013)* builds a generalized approach for intelligent *FDe* and recovery of power electronic system faults at the component level and fault recovery is then applied. The, short- and *OC*

faults in each power electronic component are injected in a simulation platform, and their effect on different voltage and current measurements are observed. Three basic quantities are observed for each of the measured signals: average value, *RMS* value, and harmonic content. The *FDe* and degradation of other components, such as *MOSFETs*, is studied in *(Vaalasranta et al., 2013)*. In this regard, the *FD* of *IGBTs* is studied in *(Lu, Sharma, 2009; Anderson et al., 2013; Ji et al., 2013; Sutrisno, 2013)*. *(Lu, Sharma, 2009)* provided a relatively comprehensive study for the *FDe* approaches for *IGBT* modules. *(Anderson et al., 2013)* proposes an online *Principal Component Analysis (PCA)* - based algorithm for early *FDe* in *IGBT* switches. In *(Ji et al., 2013)*, the authors propose a new on-board *CM* of the aging of solder layers in *IGBTs* for electric vehicle applications. *Sutrisno, 2013)* provided a study on building a *FDe* model for *IGBT* using *K-Nearest Neighbor (K-NN)* classification algorithm. The targeted failure mode was thermos-mechanical fatigue and the signals collected included voltage, current, and temperature.

Power electronics modules such as *inverters* and *rectifiers* are crucial in industry and they are indispensable in various *power conversion* systems. Rectifiers and inverters, have gained acceptance as core components in battery charging systems *(Yang, Choi, 2014),* uninterruptable power supplies, wind generators *(Chen et al., 2009), etc*. Switch failures in power *converters* are classified into two major groups: *SC faults*, *OC faults*, and degradation faults *(Kamel, et al., 2015).* Compared to *OC fault*, *SC fault* causes more harmful effects on converter circuit. Recently, the health conditions of the power electronics *converters* have obtained increasing attractions, since the degradation or the malfunction of these critical components might result in catastrophic failures. Extensive studies have been dedicated towards the *FDi* of *power electronics converters* in decades. Research on Research on *FDe* of the *DC-DC converters* has been done as well.

Among all types of *converters* the *inverter failures* have attracted the most attention. *(Aris et al., 1994)* used *Digital Signal Processing* (*DSP*) and knowledge based approach to detect and analyze all possible faults in *inverter* circuit by using *FL* techniques. *(Kastha, Bose, 1994)* have investigated the various fault modes of a *PWM* voltage source *inverter* system for induction motor. *(Mendes et al., 1998)* presented a Park's vector approach on detecting and diagnosing the *inverter* fault. *(An, et al., 2011)* proposed an open-switch *FDe* method for the voltage-source *inverter* based on the switching function model. The voltage related fault signature was investigated by comparing the voltage-time sequence under healthy and faulty conditions. *(Choi, et al., 2012)* presented another open-switch *FDe* method for the inverter based on the phase current.

Besides the *inverter*, researchers are also interested in other *converters*. For *rectifier FDi*, most studies have focused on both short-circuit and *OC failures*. Compared with the short-circuit fault which will bring immediate system shutdown, *OC fault* induced system might not lead to downtime but degrade its performance and generate disturbances in *AC-DC* conversion. *(Ku, et al., 2012)* presented an open-switch *FDe* method and a tolerant control approach for a multi-level *rectifier.*

II.3.4.4 - Reactor Core Monitoring

The safe and economical operation of a reactor is strongly dependent on the adoption of an efficient *core monitoring system*. Especially important is to implement an accurate tool able to predict, in real time, the *core characteristics* and the *core evolution (Caruso, 2008).*

Basically, *core monitoring systems* are based on the constant monitoring of crucial parameters and on the definition of admissible operational band *(Caruso, 2008).*

The reactor core is the central part of a *NR* where nuclear fission occurs. It consists of internal structures composed of systems and components: fuel (including fuel rods and the fuel assembly structure comprising fuel bundles, *CSB* assembly, moderator, coolant, control rods, reactor core control system, the shutdown system and the monitoring system, including components and equipment used for ρ control and shutdown *(IAEA, SSG-52, 2019)*.

AREVA's simple, reliable monitoring system provides *CtM* and on-line assessment of actual core safety limits with a real-time display. This Increases the overall guidance available to operators and improves the ability to navigate transient conditions and to detect and diagnose core anomalies *(Link3).* The *SCORPIO* system *(Berg et al., 1987; Berg et al., 2000)* was elaborated in the early 1980s, it has been operating in nine *PWR* units *(Molnár, Sikora, 2013)* in Sweden, *UK*, *USA*, *Czech Republic*. Among features of the *SCORPIO* system are validates measured data and identifies sensor failures, prediction of critical parameters, optimum combination of measurements and calculations to obtain precise values of important parameters and integrated modules for monitoring fuel performance and coolant activity for identification of fuel failures.

A - Monitoring of reactor internals vibration

To achieve a high level of safety while maintaining an important level of plant availability, it is desirable to perform preventive measures instead of corrective ones. One of these measures is to monitor internal vibration characteristics of the reactor. It is difficult to measure vibrations of reactor internals directly, but it is still desirable to obtain such information indirectly because excessive vibrations pose risks to their structural integrity.

Core motion monitoring is intended to encompass all moving parts of the reactor core and surroundings, with both solid and fluid motions being included. This therefore entails movements of fuel, in-core structure, control rods, core support structures, coolant moving through the core and within the vessel *(Thie, 1979).* During normal operations of a *NPP*, the *CSB* moves with infinitesimally small amplitudes by the random thermo-hydraulic load of reactor coolant flow *(Song, Jhung, 1999).*

The *core barrel* in *PWRs*, which is a structure hanging vertically inside the reactor pressure vessel from its top, might vibrate during operation of the plant. Excessive vibrations might indicate some wear of some mechanical components in the vessel, especially at the radial support of the core barrel and core support plate. Furthermore, *Flow-induced vibrations* of reactor core components have been a major cause of failure of reactor internals in many *NPPs* *(Ansari et al., 2008).* There are a large number of components, For example fuel rods and control rods, which can undergo flow induced vibrations during normal operation *(Sankoorikal, 1986).* Also, the excessive motion of fuel assemblies has led to fuel rod cladding failure in a number of *PWRs* *(Sankoorikal, 1986).* It is thus of prime interest to monitor and diagnose *core barrel vibrations* *(Demazière, 2017).* Last decades, the monitoring of core-barrel vibrations caught attention *(Arzhanov, Pázsit, 2003; Sunde et al., 2006)*.

Control rod vibrations have also been observed in reactors. This may lead to poor performance or unavailability of the rods in an emergency, or to damage the core structure *(Sankoorikal, 1986).* In all reactors, substantial attention is given to the surveillance of control rods, considering their importance to safety and the general proneness of actively moving (rather than passively stationary) components to malfunctions *(Thie, 1979).*

(Roston et al., 1996) focused on the study of a neutron noise based technique for the *FDi* of reactor core internal, in particular, excessively vibrating control rods. The application of a *NN* technique to determine the rod position from the detector spectra is much faster, more effective and simpler to use than the conventional method.

One method to monitor the vibration of reactor core is by analyzing the *neutron flux* or *neutron noise* sensed by *ex-core detectors* around it as demonstrated by *(Yun et al., 1990)*. *NR*s are equipped with *ex-core neutron flux detectors* for reactor control and protection. Many reactors also have *in-core neutron flux detectors* for monitoring the in-core neutron flux distribution *(Rouben, 1999)*.

Signals from sensors and neutron flux, associated with process variables in a *NR* show fluctuations around a mean value, commonly called *noise* *(Sankoorikal, 1986; Ansari et al., 2008).* This *noise component* is caused by *perturbations* in the *reactor core*, which result in *neutron flux fluctuations*. The movement of an absorber in a reactor induces neutron density fluctuations *(Weinberg, Schweinler, 1948)* and any mechanical or thermal-hydraulic

disturbances in the reactor core are transformed in the fluctuations in ρ and neutron flux due to the ρ-power transfer function *(Ansari et al., 2008).* These perturbations appear in the noise in the signals of the neutron detectors.
Hence, *reactor NA* or *NNA* is based upon the monitoring of the deviations of typically the *neutron flux* from its mean value *(Demazière, 2017).* These fluctuations, deviation or perturbation, carry information regarding the behavior of components inside the reactor core. Therefore, proper analysis of this noise can be used to determine information about the source provides, an effective way to *diagnose abnormal vibrations* of *reactor internals* and give an insight into the phenomenon occurring in the core *(Ansari et al., 2008).* From the analysis of noise spectra, it is possible to estimate the motion of reactor components during reactor operations. Generally, it is known that resonant peaks exceeding 1 *Hz* in the neutron noise spectra are caused by the mechanical vibration effects *(Fry et al., 1984)*.
The analysis of reactor noise requires the knowledge of various *noise sources* in the reactor that *affect the* ρ of the system. The *mechanical vibration* of the *fuel elements* or *control rods* has been identified as one major source of neutron noise. The fluctuations in *coolant temperature*, *flow* and *pressure* also contribute to the ρ and neutron noise in *NPP*s *(Ansari et al., 2008; Figedy, 2011).* One of the challenges of noise *FDi* is nevertheless to be able to recover from very few neutron detector signals the nature and characteristics of the driving perturbation, localize it, and classify the severity of the anomaly. This requires competences in many areas, such as reactor physics and dynamics, reactor modeling, stochastic processes, signal analysis, and measurement techniques *(Demazière, 2017).*

NNA has been extensively studied since the 1960s *(Kolbasseff, Sunder, 2003)*. The reactor noise has been employed on-line while the reactor is running at nominal full power conditions for the development of advance reactor core surveillance systems. *NNA* has also been studied for vibration monitoring of *PWR pressure vessel*, flux detector guide tubes *(Arzhanov, Pázsit, 2002)*, *fuel bundles*, and *control rods* *(Czibok et al., 2003)*. Identifications of *PWR CSB* vibration using *ex-core neutron detector noises* are presented in *(Park et al., 2003)*. The application of *Neutron Noise Analysis* (*NNA*) to the ex-core neutron detector signal for monitoring the vibration characteristics of a reactor *CSB* was investigated in *(Robby et al., 2015).*
Much research has been done to monitor the *CSB's* vibrations. *(Song, Jhung, 1999)* utilized the analytical finite element model to calculate the *CSB's* frequency response function and validated it experimentally with a modal analysis experiment on a scaled-down model of the *APR*1400's *CSB*. The modal analysis was done by a shaker test using vibration sensors attached to the *CSB* model. Further research conducted by *(Ansari et al., 2008)* correlated the ex-core detector data and vibration sensors mounted on reactor structure and control rod drive mechanisms. As a result, they were able to identify a particular control rod that had a different vibration signature. They also concluded that the use of ex-core *NNA* was more sensitive in determining the dynamic behavior of reactor internals compared to the vibration sensors. In *(Ansari et al., 2008),* a *reactor Internals Vibration Monitoring System* (*IVMS*) has been developed for *NPP* surveillance. The system detects the *core barrel motion* and *flow-induced vibrations of reactor internals* by analyzing the inherent fluctuations (reactor noise) present in the neutron flux signals from ex-core neutron detectors. The magnitude of the displacement of vibrating control rod has also been calculated from the measured *PSD* of neutron noise. Furthermore, the measurements have provided experimental validation of neutron noise technique for detection of flow-induced vibrations of in-core components.
WT and *Time-Frequency Analysis (TFA)* have been considered for advanced *NNA*; for example, *(Arzhanov, Pázsit, 2002)* presented applications of wavelet-based analysis of neutron noises to detect and quantify impacting of instrumentation tubes with nearby nuclear fuel assemblies in *BWR* due to excessive tube vibrations.
A research project published in *NUREG/CR*-5501 (1998), “Advanced Instrumentation and Maintenance Technologies for *NPP*s”, investigated such *OLM* applications as *NA* for measuring the *vibration of reactor internals* and other components such as *Reactor Coolant Pumps (RCPs)* *(U.S. Nuclear Regulatory Commission, 1998)*.

The major advantage of reactor noise technique is that is a non-intrusive. It does not require any perturbation to the reactor core, since all signals are acquired at normal, steady-state power operation. Also, in many cases no additional sensors are required for noise measurements and the neutron flux. The standard existing plant instrumentation, neutron detectors and sensors for temperature, flow and pressure signals are used *(Sankoorikal, 1986; Ansari et al., 2008).*

In addition, *neutron detectors* have proved to be more sensitive than accelerometers in measuring the *vibration of the reactor vessel* and its *internals*. This is because the frequency of vibration of reactor internals is normally below 30 Hz, which is easier to resolve using neutron detectors than accelerometers. Accelerometers are more suited for monitoring higher-frequency vibrations *(Hashemian, 2011).*

B - Process Parameters Validation

In *NR*, sensor outputs from many different channels are used in control, protection and plant-wide monitoring systems. Therefore, it necessary to validate sensor signal signals to increase the reliability of these systems and operator decisions. Signal validation is used to check the consistency of the redundant measurements of selected process variables, estimate their expected values from measurements, and detect, isolate, and characterize type of the anomaly in the measurement channel outputs. So, for sensor signal validation and process monitoring problems, the prediction of one or more process variables in a system is necessary*(Eryürek et al., 1991)*.

For signal validation the promising candidate is the *Neuro-Fuzzy* (*NF*) *system PEANO*, which is the product of the *OECD Halden Reactor Project*. *PEANO* *(Fantoni et al., 1998)* has originally been developed for various *process parameters validation*, like *power*, *pressures*, *temperatures*, *flows*, *water levels, etc*.

As demonstrated in the literature *(Mazrou, Hamadouche, 2004; Mirvakili et al., 2012),* a *NN* surrogate model can *predict reactor core parameters* with sufficient accuracy at only a fraction of the computation time. In *(Hedayat et al., 2009)* a very fast estimation system of four core parameters, to optimize reactor core adequately, has been developed by using cascade feed forward type of *NNs* (*NNs).* These parameters are k_{eff} when control rods are completely out of the core, k_{eff} when control rods are completely in the core, *power peaking factor* and *maximum thermal neutron flux.* Results are compared with the results of *(Mazrou, Hamadouche, 2004)* in using *NN*s in prediction of two safety parameters, *Keff-out* and *PPF*, in research. In *(Schlünz et al., 2015)* *NN* surrogate models are constructed for the *prediction* of *core parameters* for the *SAFARI-1 NRR*. The parameters correspond to possible *In-Core Fuel Management Optimization (ICFMO)* objectives and constraints. *(Figedy, 2011)* outlined *two approaches* to *in-core SeV*. The *first approach* is based on the assumption that most of the *perturbations* in a *NR core* affect the layers of the core containing the *in-core sensors* and that these perturbations are characteristically correlated. It is assumed that the *decreasing similarity* of signals prompt components is the manifestation of a *sensor failure*. The results showed the applicability of *linear CCs* and *mutual information* based criteria to *SPNDs* and thermocouples signal failures detection. The *second approach* is based on the *NF system PEANO* trained to residuals, *i.e.,* the differences between the core simulator physics code results and the experimental values. In *(Mori et al., 2003)* various up-to-date *SP* algorithms are introduced to compensate for a lack of information in order to monitor in-core status from a limited number of signals. These algorithms, such as independent component analysis, factor analysis and model based parameter estimation, are demonstrated to be effective through real plant data analysis to evaluate *core and regional stability index*, *ρ coefficients* and *core FR*. Through these practices, the authors demonstrated that the *core noise monitoring system* is an effective general platform for providing a variety of monitoring. In *(Caruso, 2008)* an overview of the *on-line core monitoring* and analysis system used at the *Beznau PWRs* is illustrated, discussing the main criteria and engineering solutions to be followed to optimize the plant operations and to improve the reactor safety. This core surveillance system, *GARDEL*, combines advanced prediction tools (*CASMO*-4/ *SIMULATE*-3) for 3*D* core simulation with an efficient monitoring system.

C - Power Monitoring

Power monitoring in *NR* play a major role in safe reliable operation of *NR*s and accurate *power monitoring* using advanced developed channels could make *NR*s a more reliable *(IAEA, 2008)*. *Chap. I* gives more explanation of the power monitoring and its importance. *Power monitoring* of *NRs* is normally done by means of neutronic instruments, *i.e.,* by the measurement of *neutron flux* which is always done by means of nuclear detectors, calibrated by thermal methods. The greater the number of channels for power measuring the greater is the reliability and safety of reactor operations. Redundancy and diversity are two important criteria for power measurement in *NR*s. Other criteria such as accuracy, reliability and response speed are also of major concern *(Mesquita et al., 2012)*. Furthermore, the *power monitoring* can be done by using the *temperature difference between an instrumented fuel element* and *the pool water below the reactor core*. The *Tf measuring* is the most reliable way of *OLM of the reactor power (Mesquita et al., 2009)*. Another method consists of the *steady-state energy balance* of the primary and secondary reactor cooling loops. The thermal balance method is now the standard methodology used for *IPR-R1* reactor power calibration *(Mesquita et al., 2009)*. A further method is the *calorimetric procedure* whereby a constant reactor power is monitored as a function of the temperature-rise rate and the system heat capacity. Another methodology, which does not employ thermal methods, is based on measurement of *Cherenkov radiation* produced within and around the core *(Mesquita et al., 2012)*.

In *(Mazrou, Hamadouche, 2004)*, authors have developed a comprehensive computational system based on the use of a *BPNN* to predict two safety core parameters in *Light Water Research Reactors* (*LWRRs*) which are the *multiplication factor* and *fuel power peaks*.

D - Reactivity Monitoring

We recall that the ρ monitoring is treated in *Chap. I.* Generally, a ρ measurement system in *NR* consists of external neutron detectors and ρ meter. The neutrons leaking from the reactor core come into the external detectors and generate electrical current. The ρ meter receives the amplified current and makes a real-time inverse kinetics calculation, during which the spatial correction and dynamic correction will be added. Normally, the whole measurement and calculation cycle is conducted once in each time step of 0.1 or 1*s* *(Xingkai et al., 2019)*.

*NR*s must have sufficient excess ρ to compensate the negative ρ feedback effects such as those caused by the *Tf* and power defects of ρ, fuel burnup, fission poisoning production, and also to allow full power operation for predetermined period of time. To compensate for this excess ρ, it is necessary to introduce an amount of negative ρ into the core which one can adjust or control it at will. In the *IPR-R1* Reactor the ρ control is done by three control rods that can be inserted into or withdrawn from the core *(Mesquita, Souza, 2010)*. One indication of the core ρ is the *Effective Multiplication Factor* (k_{eff}), the most important measure. The k_{eff} is defined as the ratio of the neutrons produced by fission in one generation to the number of neutrons lost through absorption and leakage in the preceding generation *(Jiang et al., 2008)*.

In *(Jiang et al., 2008)*, a *NN* is used to predict the k_{eff}, an indication of the ρ of a *NR*, given a fuel Loading Pattern. In nuclear engineering, the k_{eff} is normally calculated by running computer models, *e.g., Monte Carlo* model and finite element model, which can be very computationally expensive. *(Arul, 1994)* applied *NNs* to the task of ρ monitoring in a *NR* to improve the safety and the reliability of the operating plant. The adaptability of the network to slow variations in the system parameters and its ability to learn in a noisy environment are studied.

II.3.4.5 - Loose Part Monitoring

One of the major concerns during the operation of any reactor is the possible presence of *LPs*. Recently, most of *PWR* of the world have been equipped by *Loose Part Monitoring Systems* (*LPMS*) *(IAEA, 2008; Olma, 2003; Michela, Puyala, 1988; Por, 2016).*
LPs are disconnected or forgotten objects in the primary loop of *NRs (Por, 2016).* A *LP* in a *NPs may result* from a *deteriorated component* somewhere within the *flow circuit* or from an *item* (*e.g.,* a tool) inadvertently left in the primary system during construction, refueling, or maintenance *(Vahaviolos, al., 2008).* Nuts, bolts, pins, sections of tubing, and hand tools used in maintenance have been found in the primary coolant systems of *PWRs (Rhodes, Langenberg, 2012).* A *LP* can come from internal structures of the *Reactor Coolant System (RCS)* due to corrosion, fatigue, and friction. It can also be introduced externally during refueling and maintenance tests.
If introduced inside the plant's flow, the *LP* can contribute to *component* (*e.g.,* tube or valve) *mechanical damage* and material wear by frequent impacting with other parts in the system (*e.g.,* contact the walls of the tube) which may, eventually, result in a leakage *(Vahaviolos, al., 2008). LPs* drifted with the speed of the stream of water can be broken into small pieces therefore, they can damage reactor internals and reactor coolant pumps *(Rhodes, Langenberg, 2012).* They can also reach the reactor core, and disturb the motion of control rods and partial block the coolant channels *(Por, Szappanos, 2000; Gor, 2005).* The latter can lead to overheating of the fuel elements. Therefore, *LPs* may pose serious threats, and trigger major problems in the nuclear system operation, necessitating repairs costing millions of dollars *(Szappanos et al., 1999; Rhodes, Langenberg, 2012).*

LPMS is a monitoring device that detects the shock wave generated from the collision of *LP*s and pressure limitation internal structure by mounting accelerometer (shock wave sensitive sensor), where *LP*s gather naturally. *LPMS* is used at *NPs* to detect the onset *LP*s within the *RCS*, locate the *LP*s, and estimate their mass and potential damage. The *LPMS* provides alarms, signal displays, and data to plant personnel. Depending on the nature of the *LP*, appropriate decisions can be made on what actions should be *(Rhodes, Langenberg, 2012).*
Early detection of such *LPs* during operation is a key issue in order for plant management to schedule preventive actions prior to significant damage and catastrophic failures. *LPMS* can prevent accidents such as damage of *RCS* and structure, and rod operation hindrance. Consequently, *LPMS* is an important system for *NPs* safety insurance *(Rhodes, Langenberg, 2012)* and it has been a requirement on *NPPs* for many years *(Vahaviolos, al., 2008).*
Experiences in *Pn* stations show that existing *LP* monitoring systems provide valuable information mainly during the start-up period (and in the following 1-2 months). After that period the possible *LP*s (forgotten objects) either have drifted to some traps where they rest or get stuck in structural elements, or they break into small pieces. In either way there is no much *LP* activity after a couple of months of operation. For this reason, in most of the *NPs* the *LP* monitoring systems are switched off during normal operation *(Por, Szappanos, 2000).*

Detecting and diagnosing a *LP* mainly relies on *acoustic signals* generated by the impact of the *LP* with the *RCS* pressure boundary. Impacts on the inner walls of the *RCS* are manifested as bursts in the sensor output signals. The acoustic signals are detected by *AE* sensors (*e.g.*, accelerometers) located at selected positions on the outer *RCS* boundary, reactor coolant pumps, and possibly on other components of the RCS. When a *LP* is found in one loop, it is more desirable to connect the sensors of the same loop where the event was found - this can give an optimal performance both for source location and *LP* mass estimation *(Por, Szappanos, 2000).* Because the bursts are embedded in the high-acoustic background noise of the *RCS*, identification and localization of *LP*s is a difficult task. *(Rhodes, Langenberg, 2012).* Filtering techniques are typically used for pre-processing to remove background noises. *LP* detection relies on comparing the pre-processed signal with a pre-set threshold. Time delays between sensor pairs that detect the same event provide information to locate the *LP*.
Identifying the precise location of a *LP* is still a challenge for existing *LPMSs*. Mass estimation of the *LP* mostly relies on *Hertz* impact theory which supports the observation that low frequency signal components increase as

the mass of the *LP* increases. Therefore, the mass of a *LP* can be estimated by referring the frequency characteristics (*e.g.*, frequency ratio and center frequency) of the acoustic signal to the baseline measurements *(Yoon et al., 2006)*.

The design and implementation of an *LPMS* is a complex undertaking that requires judicious selection, integration, and installation of system components such as *AE sensors* and cabling, which must endure the hostile environment within the reactor containment for decades without significant performance diminution. Further, attainment and mastery of the proper hardware interfaces, software operating systems, and computer control codes are essential to prevention of *FAl*s without sacrificing system detection limits. Finally, highly skilled software and hardware specialists are needed to install the *LPMS* and tune it to achieve optimum performance *(Rhodes, Langenberg, 2012).*

The biggest problem of recent *LPMS* systems was the high missed alarm and *FAl* rate. This is one of the most important aspects of *LPMS* design and implementation.

Due to high *FAl* rate, operators tend to neglect the warnings coming from *LPMS*. The main cause of high *FAl* rate is the fact, that event recognition is based typically on the standard deviation (*RMS*) value or on the amplitudes of acoustic signals originated from *LP* sensors (which are, in most of the cases, accelerometers) *(Por, 2016).* One solution of this problem is introducing different methods based on observations of the signatures of the signals measured in practice. For example, more than one sensor can be used to detect *LPs* event, and the combination of thresholds for statistical moments can lead to improvement in false and missed alarm rates *(Por, 2016).* Highly developed software analyzes the *LP* transient and differentiates *LP* impact signals from noise. Modern digital systems have stringent multi-level alarm criteria, which minimize missed and *FAl*s due to noise, thus minimizing unnecessary operator distractions and the need for data analysis by a human expert *(Rhodes, Langenberg, 2012).* Using sophisticated techniques such as these to distinguish between background events and *LP* impacts, modern *LPMSs* have demonstrated *FAl* rates and missed alarm rates well below 1% *(IAEA, 2008)*. *LPMS* performance is affected by the number of sensors used, their locations, and the methods used to attach them to the wall of the *RCS*. These factors influence the ability of the *LPMS* to locate noise sources and its ability to interpret the amplitude and frequency content of detected signals *(Weiss, Mayo, 1991)*.

Present day digital *LPMS* architecture and software flexibility have allowed the integration of additional functions into the same, *PC*-based system, incorporating the capability of parallel monitoring of various critical valves in the plant. This integration offers significant advantages as compared to using two separate systems, such as economy, installation efficiency, operator friendliness, *etc.* Simultaneous monitoring of the two phenomena (*LP*s impacts and flow) also enhances signal interpretation capabilities and results in better evaluation and more solid management decisions *(Vahaviolos, al., 2008).*

It is an ongoing research topic to apply advanced *SP* methods such as *WT (Pokol, Por, 2006), TFA (Kim et al., 2003; Yoon et al., 2006),* and *NN (Figedy, Oksa, 2005)* to achieve enhanced *LPMS* performance, *e.g.,* reduced *FAl*s, more accurate time of detection, and more accurate mass estimation. *Autoregressive* (*AR*) *modeling* and the *sequential probability ratio test* (*SPRT*) are two of the most sensitive methods *to distinguish LP impacts* from *events responsible for background noise* in the *RCS (IAEA, 2008; Rhodes, Langenberg, 2012).*

(Vahaviolos, al., 2008) discussed the application and operational aspects of an integrated *LPMSs* and *Valve Flow Monitoring System* (*LPMS-VFMS*) for *NPPs*, and demonstrates how modern digital *AE* systems and processing strategies can improve *LPMS-VFMS* operation and uniquely detect and evaluate, metallic *LP*s and critical valve flow, in the presence of severe environmental noise and vibration. *(Weiss, Mayo, 1991)* describe a research project in which metal impact theory and experimental data were used to develop a quantitative description of *LP* impact signals. This approach was used to determine relationships between the amplitude and frequency content of the plate bending waves and the energy and mass of the impacting object, signal transmission characteristics, and sensor response. These relationships were used to develop recommended practices for

specifying sensors, mounting sensors, processing signals, interpreting signals, and calibrating the system *(Rhodes, Langenberg, 2012).*
For instance, *(Chang et al., 2004)* describe the development of an *LPMS* for Unit 4 of the *Ulchin Nuclear Power Station* in *South Korea*. Configurations of the *LPMS* for a *Vodo-Vodyannoy Energeticheskiy Reactor* (*VVER)* plant and a *PWR* plant are presented in *(Kim et al., 2000),* respectively.

II.3.4.6 - Transient identification

NRs are highly complex systems which are ordinarily operated monitored by human operators. In case of any undesired plant condition generally known as *Initiating Event* (*IE*), or when a *transient occurs*, such as a plant accident scenario, equipment failure or an external disturbance to the system, the operator must monitor a great volume of information from instruments (*i.e., S/Ds*) reading, which involves a large number of state variables whose behaviors are extremely dynamic, which reveal a specific type of event. A transient must be correctly identified, as soon as possible, so that proper counteractions can be taken to minimize or mitigate the negative consequences. The *objective* of the plant *monitoring system* in any potentially *unsafe scenario* is to give the plant operators appropriate inputs to formulate, conform, initiate and perform the corrective actions. However, in *NRs*, *recognizing the types of transients* during early stages, for taking appropriate actions, is critical. An automatic *TI* system can be a valuable addition to operator knowledge to safeguard the plant and to minimize the negative impacts. Furthermore, classification of a novel transient as "don't know", if it is not included within *NRs* collected knowledge, is necessary.
A *transient* is defined as an *event* when a plant proceeds from a *normal state* to an *abnormal state. TI* in *NRs* is classification of the types of transients by interpreting the main plant variables. Therefore, the correct identification of transient can be considered as a support to the operator *(Santosh et al., 2007; Oliveira, Schirru, 2011; Moshkbar-Bakhshayesh, Ghofrani, 2013).*
The *abnormal transient* in *NRs* can be *initiated* by *faults and failures* in equipment and instruments or external disturbances, which are respectively related to system deviation from the desired condition and system disability in performing the desired function *(Isermann, Ballé, 1997).* Transients' occurrence on *aged NRs* is more probable *(IAEA-TECDOC-1402, 2004)*.

Deviation of the plants from normal state due to failures or faults causes difficulty in the trend interpretation of interacting variables by operators either because the changes are too subtle, or because the changes are too fast *(Moshkbar-Bakhshayesh, Ghofrani, 2013). Early detection* will help in minimizing or even mitigating the negative consequences of such transients. It is equally important to identify the type of transient correctly. Misidentification of transients might result in incorrect action by the operator and thus leading to accident situation *(Santosh et al., 2007).* When an abnormal event needs to be identified, the *TI system* compares the evolution of the measured plant variables with the signatures of the evolution of these variables for each abnormal postulated event of the plant. Hence, the transient is classified as one of the postulated transients whose signature is closest (or more similar) to the ongoing transient, according to a given measure *(Oliveira, Schirru, 2011).* Furthermore, the *event detection* can be considered as a *PR* problem. When an event occurs starting from the steady-state operation, instruments' readings develop a time-dependent pattern and these *patterns* are different from those under normal conditions and *unique* with respect to the type of the *event (Guo, Uhrig, 1992a)*. The patterns can be different for different transients, severities, and initial conditions. However, *TI* can be processed as a *PR* problem, but the complexity of *NR* system makes it a very challenging task.
TI techniques as a method to *recognize* and to *classify abnormal conditions* are extensively used. *TI* in NRs in general can be achieved either by *MBTs*, or *model-free methods*. During a transient period, instrument outputs from *NR* may go through patterns that are different from those under normal conditions. The patterns may be varying for different transients, severities, and initial conditions. Therefore, *TI* is essentially a *PR* problem, but the

complexity of *NR* system makes it a very challenging task. regardless the recent studies related to *model- based methods* for *TI* in *NRs* *(Cholewa et al., 2004*; *Hsiao et al., 2010),* these methods in *practical applications* are *not suitable candidates* and they are still very *limited (Ma, Jiang, 2011)*. Otherwise, data-driven methods, especially *NNs* and other soft computing techniques, seems to be more appropriate for *TI* in *NRs*. The *NN* as a branch of *DDTs*, and soft computing techniques is the mostly investigated method for *NPP TI*s *(Barlett, Uhrig, 1991)*. If *transient* is too *fast* to be treated as a quasi-equilibrium, then it may be obligated to use *Recurrent Neural Networks* (*RNNs*). To deal with time dependent data, an implicit time measure or adaptive template matching algorithm were proposed *(Lin, Chang, 2011)*. Also, it is important to identify transients not considered in the training stage as unlabeled transients, *i.e.*, 'don't know' transients. Furthermore, classification of "don't know" transients can be performed by using for example *Radial Basic Function* (*RBF*) or *Probabilistic Neural Networks* (*PNN*) *(Bartal et al., 1995; Na et al., 2004; Embrechts, Benedek, 2004)*. Different schemes based on *NN* are summarized in *(Uhrig, Hines, 2005)*. Performances of several *NN* algorithms are compared in *(Santosh et al., 2007)*. Other tools such as *Genetic Algorithm* (*GA*), *FL*, *Expert System (ES) (Holland, 1992) fuzzy clustering, Hidden Markov Models* (*HMMs)* and *Support Vector Machine* (*SVM*) *(Kwon et al., 2002; Zio, Baraldi, 2005)* have also been studied and are among the most applied techniques for *TIs* in *NPPs (Moshkbar-Bakhshayesh, Ghofrani, 2013).* Preprocessing using *wavelet* signal decomposition has also been studied *TI (Roverso, 2002)*. Despite those developments, additional research is required before automated *TI* systems can be successfully used in *NPs* applications. Furthermore, *NF identifiers* can be used for *qualitative representation* of the *transients (Evsukoff, Gentil, 2005)*.

One of the early works for *TI* was based on *GA* and classical probability *(Yangping et al., 2000)*. In *(Moshkbar-Bakhshayesh, Ghofrani, 2013),* recent studies related to the *advanced techniques* for *TI* in *NPPs* are presented and their differences are illustrated. *HMM* statistical method was utilized for the classification of transients in the dynamic process in *NPPs (Kwon et al., 2002)*. In addition, *SVM* as another approach based on the statistical method was used for *TI* in *NPPs (Gottlieb et al., 2006)*. *(Santosh et al., 2007)* presented a study on various *NN* algorithms for selecting a best suitable algorithm for diagnosing the transients of a typical *NPP* to assist the operator to identify such initiating events quickly and to take corrective actions. In *(Oliveira, Schirru, 2011)* the authors have described an experimental system for the identification of nuclear transients which aims to assist operators of *NPP*s to make quick judgments and decisions about the real situation of the plant in risk situations. Recently, *NF* approach for *TI* using "jumped" *Multi-Layer Perceptron (MLP)* and *FL* was developed *(da Costa et al. 2011)*. Finally, more detailed notes related to *abilities* and *weaknesses* of different *transient identifiers* are presented in *(Moshkbar-Bakhshayesh, Ghofrani, 2013).*

II.4 - Fault Control

Contrary to monitoring, control is an active action which consists to intervene in order to resolve the problem declared by the *FDD* procedures (*Figures II.1* and *II.7*) by taking appropriate actions in order to maintain the operation and avoid damage of the process and serious consequences. Indeed, *FC* consists to *make a decision (Hwang et al., 2010)* by taking into account the condition if the evaluated fault is tolerable or not, and then make the necessary steps to *correct, accommodate* or *reconcile* the declared faults*(Persin et al., 2002; Samy et al., 2011)* (*Figure II.24*). In this context, we review the large meaning of the *FM, FDe, FDi* and *FC.*

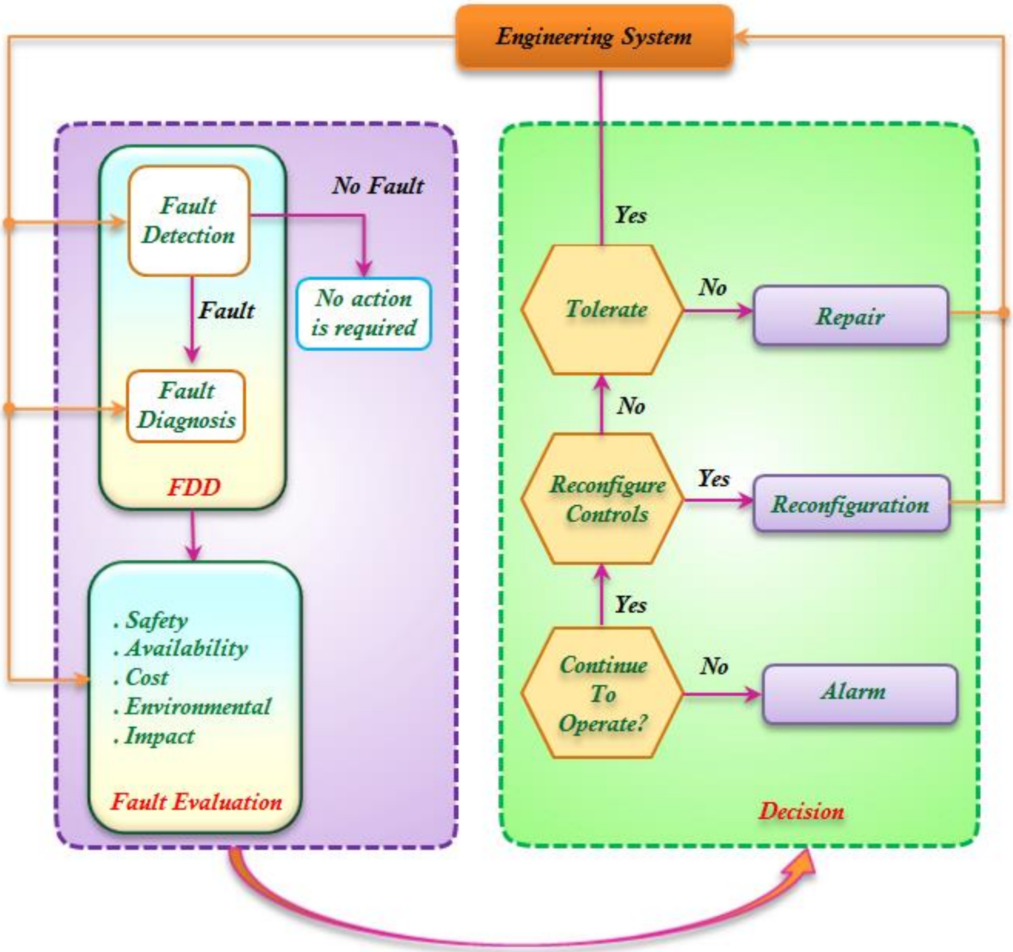


Figure II.24 - Application of FDD to the operation and maintenance of engineered systems (Katipamula, Brambley, 2005).

II.4.1 - Fault-Tolerant

Faults in automated processes will often cause undesired reactions and shut-down of a controlled plant, and the consequences could be damage to the plant, to personnel or the environment. With increasing economic and productivity demand for high plant availability, and an increasing awareness about the risks associated with system malfunction leads to more challenging operating conditions of modern engineering systems and dependability is becoming an essential concern in industrial automation. Sensor, actuator or process failures may drastically change the system behavior, resulting in performance degradation or even instability. In complex systems, dependability is as important as performances. Faults may drastically change the system behavior, ranging from performance degradation to instability.

Generally speaking, there are three methods to overcome errors and maintain the system in its normal condition. These methods are described as follows: (*a*) *fault avoidance*- it includes any technique applied to prevent fault or error. (*b*) *fault masking* – it consists of any procedure that after occurrence of fault, at least prevent the system from facing error. (*c*) *fault tolerance* – The ability of a system to continue its performance in spite of faults. It relates to reliability and successful performance. A fault tolerant system must be able to manage the faults in hardware or software components, electrical break down, or any other unexpected defects.
When a system *deviates to a degraded performance region* in *presence of a failure*, *FT system* can *recover itself* moving into an *optimum performance region*, or near to it. These systems have become increasingly important for robot manipulators, especially those performing tasks in remote or hazardous environments, like outer space,

underwater or *nuclear environments*. In *Figure II.25* we see a scheme showing the different performance regions a given system can adopt when a failure occurs.

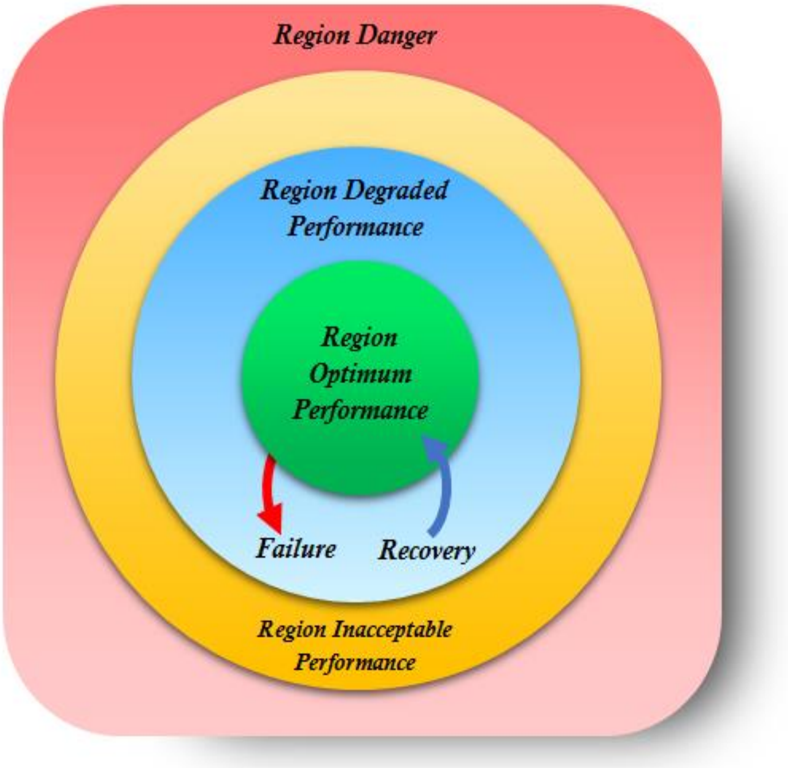


Figure II.25 - Performance regions under failure occurrence (Urrea, 2012).

FT is needed in order to reach the system objectives, or if this turns to be impossible, to assign new (achievable) objectives to avoid catastrophic behaviors. *FT* can be obtained through *Fault Accommodation* (*FAc*) or through system and /or *controller reconfiguration* (Blanke et al., 2001).

It is clear that there are weight, power, size, and economic penalties associated with a *HR* approach to the design for *FTo* capabilities. *FTo* system comprises two cascaded working modules, namely *FM*, and *FAc* as shown by *Figure II.26* (Jain, Yamé, 2013). The first module is used to detect, isolate, and identify the occurred faults, while the job of the *FAc* is to accommodate the aftereffects of the occurred faults based on the information obtained from the *FDD* module so that the system can still deliver the specified performance. One of the biggest challenges in this cascaded working structure is to handle effectively the model uncertainties appearing during the *FDD* operation, which can lead to *FAls*. In addition, the strong dynamical interaction between the *FD* module and the *FAc* module is quite known in this classical scheme, which also imposes some difficulties from the real-time point of view (Jain, 2012).

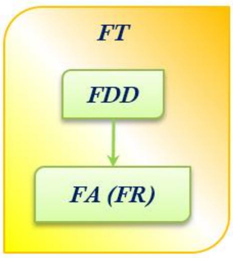


Figure II.26 - Composition of FTo system.

II.4.2 - Fault -Tolerant Control

For *Fault-Tolerant Control* (*FTC*), an early review paper was presented by *(Stengel, 1991)* in 1991, which introduced the basic concepts of *FTC* and analyzed the applicability of *AI* (*e.g.*, *NN* and expert systems) to *FTC* systems. In 1997, an overview of *FTC* was given from the system development view *(Blanke et al., 1997).* In the same year, a comprehensive review was contributed by *(Patton, 1997),* which presented the key issues of the *FTC* systems and outlined the state of the art in this field. Reconfigurable *FTC* systems are reviewed extensively respectively by *(Jiang, 2005; Lunze, Richter, 2008; Zhang, Jiang, 2008).*

FTC is the ability of a controlled system to maintain control objectives, despite the occurrence of a fault. A degradation of control performance may be accepted. *FTo* can be obtained through *FAc* or through system and /or *controller reconfiguration* *(Blanke et al., 2001). FTC* is the synonym for a set of recent techniques that were developed to increase plant availability and reduce the risk of safety hazards. Its aim is to prevent that simple faults develop into serious failure. *FTo* merges several disciplines to achieve this goal, including on-line *FDi*, automatic condition assessment and calculation of remedial actions when a fault is detected. The envelope of the possible remedial actions is wide *(Blanke et al., 2000).* The main objective of any *FTC* system is to ensure a dependable system *(Jain, Yamé, 2013).* An *FTC* is designed, in order to stabilize the closed-loop system by compensating for the effect of the fault *(Zhang et al., 2011).*

FDD and *FTC* for dynamic systems have been the subject of considerable interest and an area of intensive study in the control research community *(Isermann, 2006)* and references therein. Many successful process data-based algorithms and their applications have been reported in the literature. Hence, *FDD* and *FTC* have now become an integral part of industrial process control *(Wang et al., 2009a).*
The purpose of *FDD* is to use available *signals*, *data* or *knowledge* to *detect*, *identify*, and *isolate* possible *faults* of *sensor*, *actuator*, and *system*. Conversely, *FTC* calculates the required actions (either *controller modification* or *reconfiguration*) so that the system can still continue to operate safely even under faulty conditions *(Diao, Passino, 2001; Jiang, 2005).* Therefore, a system can be *FTo* if it is reconfigurable *(Khireddine, 2014).*
Due to the growing demands for system reliability, *FDIso* and *FTC* algorithms and their applications to a wide range of industrial and commercial processes have received considerable attention over the in recent decades. Fruitful results can be found in several excellent books *(Blanke et al., 2006; Ding, 2008),* survey papers *(Frank et al., 2000b; Staroswiecki, 2008)* and the references therein.

Generally speaking, *FTC* approaches (systems) can be further classified into two categories: *passive* (*e.g.,* robust control) and *active* (*e.g.,* adaptive control) as shown by *Figure II.27* *(Samantaray, Ghoshal, 2008). Passive FTC (PFTC),* considers systems faults as a special kind of uncertainties. It utilizes a fixed gain controller to tolerate predefined faulty operations while maintaining desirable stability and performance properties *(Yue, Lam, 2004; Gao et al., 2008). PFTC* is based on the ability of feedback systems to compensate perturbations, changes in system dynamics and even system failures *(Benosman, 2011).* It considers a robust design of the feedback control system in order to immunize it from some specific failures *(Patton, 1997). Active FTC (AFTC)* is centered in on-line failure, that is, the ability to identify the failing component, determine the kind of damage, its magnitude and moment of appearance and, from this information, to activate some mechanism for rearrangement or control reconfiguration, even stopping the whole system, depending on the severity of the problem. Therefore, an *AFTC* reacts to the system component failures actively by reconfiguring control actions so that the stability and acceptable performance of the entire system can be maintained. Typically, an *AFTC* needs a *FDIso* scheme to identify the fault-induced changes, and a mechanism to on-line accommodate the control law in response to the *FDI* decisions *(Blanke et al., 2006; Zhang, Jiang, 2008).* In contrast to *PFTC*, *AFTC system* have in general better *FTo* capability, and hence have received more attention.

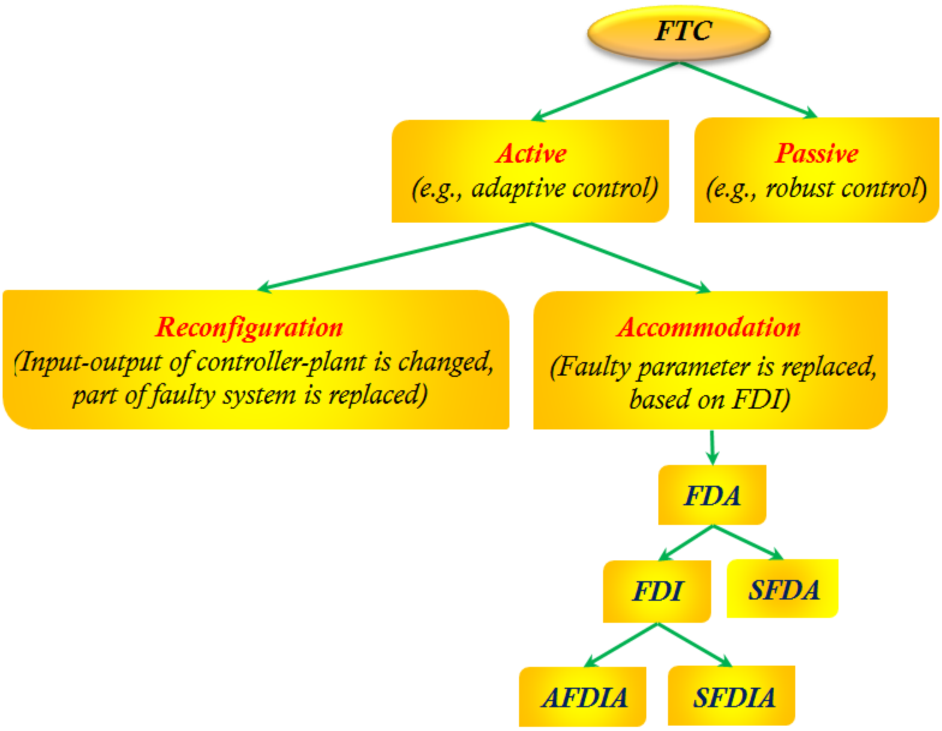


Figure II.27 - Sorts of FTC (Blanke et al., 2001, Samantaray, Ghoshal, 2008).

AFTC approaches, which rely on early detection of faults, are able to improve the efficiency and the reliability of such processes. It is obtained by *FAc*, which controls the faulty system, or by *reconfiguring* the structure with *System Reconfiguration* (*SR*), which controls the healthy (reconfigured) part of the system *(Staroswiecki, Gehin, 2001; Zhang et al., 2011)* in the presence of faults.

Some results on *FTC* for *NL systems* were reviewed by *(Benosman, 2010).* Along with *FDi*, brief reviews on data-driven *FTC* and model-based *FTo reconfiguration* were presented by *(Wang et al., 2009; Hwang et al., 2010)* respectively. From the viewpoint of industrial applications, fault tolerance techniques were reviewed for electric drive systems *(Campos-Delgado et al., 2008)* and power electronics systems *(Song, Wang, 2013; Mirafzal, 2014).*

II.4.3 - Validation, Recovery

In large power generating systems and process control systems, *sensor* outputs from many different channels are used in *control systems*, *protection systems* and plant-wide *monitoring*. Sensors enable the simple collection of data, but these devices must still provide the right information at the right time for *FDe* and avoidance. If necessary, to *validate* these signals to increase the reliability of operator decisions, *SeV* is one of the ways that can help to improve the reliability of control and protection systems *(Eryürek, Türkan, 1991).* To do that, it is necessary to *validate* the measured sensor data, *isolate* any failed sensor and *recover* the failed sensor measurement before they are used (*e.g.,* by the controller. In these safety-critical processes, data must be first *validated* and/or *accommodated* (when data are proven to be invalid) before any work is to be done using these data. So, a reliable *FM* method should be able to *validate* its input data prudently, so that a consistent, high-quality *monitoring* can be maintained.

Erroneous and *conflicting* sensor readings often *confuse* human *operators*, *degrade* the *performance* of control systems, and may lead to actions that compromise the *safety* of *NPPs*. The installation of *redundant sensors* for safety related parameters is a *standard* instrumentation *practice*; assessing measurement *validity* of enormous sensors by human operator is, however, tedious and its effectiveness is heavily dependent on operator's training and attention level. Therefore, there is a need to use *modem computer-aided techniques* to automate the *validation* process.

SeV refers to the capability of detecting, isolating and reconstructing a faulty sensor. For *SeV* and process monitoring problems, it is necessary to predict one or more process variables in a system. The estimation of system variables is performed by either using physical or empirical models for validating instrumentation outputs and process monitoring. *SeV* and process monitoring problems in many cases require the prediction of one or more process variables in a system. *SeV* requires that an *expected* value be generated for a sensor's reading. This *expectation* needs to be *based on reliable sources* of *information* other than the sensor itself. Then, the *residual* between the expected and actual values is computed, and processed through fault-*detection* logic. If no fault is detected, then the sensor reading is declared valid. If there is a fault, then it needs to be identified and isolated. *SeV* is used to check the consistency of the redundant measurements of the selected process variables, estimate their expected values from measurements, and detect, isolate, and characterize the type of the anomaly in the measurement channel outputs.
SeV in the broadest sense is related to reliability, namely *determination* that a *sensor* (or a configuration of sensors) is or is *not providing* the *correct signal*. If the signal is not correct, we would like to be able to distinguish between a *faulty sensor* and a *faulty condition* of the process being measured.
Validating a sensor signal means proving and documenting the proof that the sensor (or instrument) consistently does what it purports to do. What this means is that the sensor must be shown to consistently provide the correct temperature, pressure, *etc*., and analysis by the validation hardware or software should provide an alarm that the sensor signal deviates from the correct value. Then, a human can decide whether to remove the sensor from being on line, or adjust the signal, or take some other action.
Usually, redundant sensor with voting schemes are used for those sensors likely to fail and for critical sensor used in the control loop. In some cases, it may not be feasible to have multiple sensors for the same measurement due to physical limitations or due to the specific operating condition. In such cases, the *AR* makes it possible to *validate measured data*, *identify sensor failure*, and *recover failed measurements* *(Ray, Luck., 1991)*. A well-known technique involving *AR* is a special designed *KF* which has been used to *Sensor Failure Detection and Accommodation (SFDA)* in the *jet engine control* *(Merrill et al., 1988)*.
SeV has other attributes such as *FDi* of the physical cause (s) of the fault, a list of *actions to take* in priority in order to remedy the fault, and ways to *ameliorate* the fault by *substitution*, *recalibration*, or *control action*. Even *maintainability* can be considered *part* of the task of *SeV*.

In addition to *SeV*, we find in literature *Sensor Recovery* and *Virtual Sensor Networks* as part of the overall predictive health maintenance system. The recovery consists in finding the remedy for the failure. In the simplest case, it is the replacement of the faulty element *(Olivier-Maget, 2007)*.
Sensor recovery will predict the values of sensors that were detected as faulty by the *SeV* process. Furthermore, *data recovery* is the process of restoring (reconstruct) data that has been lost, accidentally deleted, corrupted or made inaccessible. The *Virtual Sensor network* will be used to predict values of those sensors that are present in development but absent in production *(Uluyola et al., 2001)*.
When a *critical sensor* reading is found to be *erroneous*, it is necessary to *estimate* its *true value* using correlated measurement. A simple approach is to have one estimation relation for each sensor reading that needs to be *recovered*. The *recovery rate* (*RR*) is given by:

$$RR = \left(1 - \frac{|Y_{SFDIA} - Y_{TRUE}|}{|Y_{TRUE}|}\right) 100\ \% \tag{II.1}$$

where Y_{SFDIA} and Y_{TRUE} represent, respectively, the *Sensor Failure Detection, Identification and Accommodation* (*SFDIA*) accommodated and the original true performance.

To *reduce* the *effects* of *sensor faults* on the process control, it is interesting to *devise* a *SeV* scheme to three steps: *FDIA*. (*a*) In a real physical system where faults can occur, how do we *detect* when the information provided to the control system *through* the *measurement system* is *incorrect*. (*b*) Once it is known that something is wrong with the presented information, how do we *identify* the faulty sensors and *isolate* the source of the problem. (*c*) Once it is known *where* the *problem* is, (which sensor has failed), how do we *accommodate* the problem by replacing the biased measurements with an estimate of the correct value *(Duane et al., 1998; Baraldi et al., 2010)*. *(Ning, Chou, 1992)* gives a list of critical signals and the associated sensors to be validated, according to the *Piping* and *Instrument diagram* of the *Maanshan NPP*.

The *SiV* methodology uses redundant measurements that may be either *direct sensor* outputs or *analytically* obtained from a *MM* formulated on the basis of physical relationships among other process variables (*e.g., mass* and *energy balances* in *thermal-fluid processes*). It provides a unified systematic procedure for *FDIR* and *sensor calibration* and *measurement estimation*. Many *MMBAs* have been applied for sensor *data validation* for *FDe* *(Mandal, 2015)*.

Two common methods for *SeV* are *PCA* and *Partial Least-Squares (PLS);* however, since they are *linear methods*, they are *optimal* only for *Linear Systems (LSs).* Another option is *KFs*, which were also developed for *LSs* but can be *extended* to cope with *NL systems*. However, *KFs* are *model-based* (*i.e.*, not *data-driven*) and cannot be constructed with, for example, operational data. The *success* of *KF* models for *SeV* is therefore dependent on the *fidelity* of the system or *component model*.

(Guo, Musgrave, 1995) proposed new approach which utilizes the concept of the *Auto-Associative Neural Networks* (*AANNs*) for *SeV*. A *SeV approach* based on *PCA* was developed in *(Qin et al., 1997)* and was applied within the problem of *monitoring* the emissions of a boiler. In *(Mattern, Jaw, 1998)* the *SeV* problem is introduced and *two approaches* to the problem are presented: a *model-based* approach using a *NL observer*, and an *AANN.*

One of the computer-aided *SeV* approaches is to construct a *FDe* network in which sensors and system dynamic models are linked in a tree structure and processed via *analytic redundancy* and *parity relations*. Based on this approach, *(Meijer, Pasquenza, 1981)* developed an *on-line plant SeV system* for steam generator instruments of *PWR*. *(Kujawski et al., 1987)* further incorporated the technique with heuristic rules and reliability analysis for *FDi* of vessel level instruments of a *BWR*. *(Benedict et al., 1987; Deutsch et al., 1987)* used similar techniques to *validate signals* that are related to critical safety functions for the *safety parameter display system, (SPDS),* of a *PWR* as well as a *BWR*.

For *SeV* and plant-wide *monitoring*, *NNs* offer several *advantages* compared to traditional *empirical methods* *(Eryürek, Türkan, 1991). NNs* are currently being used in *many real-time monitoring* or control problems *(Roemer, 1998).* Although *NN*-based *FDi* tools can tolerate a certain degree of corruption or incompletion in data input. The *AANN* approach has often been used in *SeV (Lu, Hsu, 2002).* This *NN* method belongs to the so-called *NL PCA* category. Noise contained in the input nodes is eliminated in the mapping part located between the input and the bottleneck layers. The reconstructed data, however, are generated in the subsequent de-mapping layers beyond the bottleneck layer.

(Kramer, 1992) discusses a method for *training* the *NN* with *fault data* to filter fault information, which can significantly increase the size of the training set. The idea is that if one sensor is bad, there is enough information in the remaining sensors that the *NN* can provide accurate estimates of all the measurements, where the focus is on the bad sensor. When the *NN* is used for *SeV*, it would appear in the feedback loop of a closed-loop system as shown in *Figure II.28*. The ability to combine *FDIA* in one step is the key *advantage* of *NN*-based *SeV scheme*.

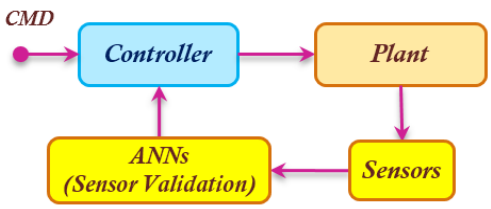


Figure II.28 - NN for SeV.

The actual implementation of a *NN* for *SeV* is not straight forward. Different approaches are suggested for the *SeV steps* that are: *FDIA*. Some approaches and ideas are presented by *(Xu et al., 1999; Ogaji et al., 2002). (Palmé et al., 2011)* evaluated an alternative approach to *SeV* in *NL* systems.

In *(Menke, Maybeck, 1995)* a *bank of KFs* was used to provide probabilistically weighted parameter *estimates* of *measurements*. This approach required a dither to disturb the *system* from a quiescent state in order to identify the system on-line. As an alternative, an *AANN* was used for *SeV* of a rocket engine in *(Guo, Musgrave, 1995).* This reference indicates that the *NN estimates* of the sensor values could be used to *replace failed sensor* values in a feedback control system. The presented work is a continuation of the work in reference *(Mattern et al., 1997)* and is based on the work in *(Kramer, 1992; Guo, Musgrave, 1995).*

(Duane et al., 1998) have presented two approaches to the *SeV* problem: a model-based approach using an *AANNs* and a *NL* observer. The latest uses functional approximation *NN*s to model the variation of the system with the operating point. The functional approximation *NNs* were used as part of a *NL*, model-based approach to *AR*. The *AANN* was used as part of an *FDIA* scheme that acted like a fault filter and only required the addition of some thresholding logic *(Mattern, Jaw, 1998).* In 1991, Kramer succeeded in applying *NN* to data compression by feature extraction without sacrificing the *non-linearity* in the data and in *NN*. He extended the potential area of application of the method to *SeV* and named it *AANN* which is an identity mapper, containing *three hidden layers* with the following functions: *mapping*, *data compression* and *de-mapping*. The use of *AANNs* for *SeV* has been proposed by *(Kramer, 1992)* and used subsequently by other researchers *(Mattem et al., 1997; Hines et al., 1998). AANNs* develop an internal compressed representation of the data which allows the network when a set of new inputs is provided, to predict outputs based on what it learned. The *residuals* between the network input and output can be used to detect input (sensor) faults. *(Hines et al., 1997a)* has used *AANNs* for *SeV*. In *(Uluyola et al., 2001) data* from *sensors* that are classified by *covariance* and *NA* are used as inputs/outputs to *AA* and/or *hetero-associative SeV networks*. These networks together with the *residual* analysis are used for *validation* and *recovery* of an *auxiliary power unit*, *APU, pressure* and *temperature sensors*. In *(Guo, 1996),* an *AANN* was used for the *SeV* of the *F100* turbofan engine. In the *AANN*, the *redundant sensor information* is *compressed*, *mixed* and *reorganized* into a smaller number of network nodes in the first part of the network. The compressed information is then used to regenerate the original redundant data at the output. Due to the information mixture, if a sensor fails, other sensor data still provide enough information to generate a good estimate to replace the faulty measurement. *(Mattern, Jaw, 1998)* presented the results of applying *two* different *types* of *NNs* in two different approaches to the *SeV* problem. The *first* approach uses a functional *approximation NN* as part of a *NL observer* in a model-based approach to *AR*. The *second* approach uses *an AANN* to perform *NL PCA* on a set of *redundant sensors* to provide an *estimate* for a single *failed sensor.(Duane et al., 1998)* have presented two model-based approaches to the *SeV* problem using an *AANNs* and a *NL* observer. The latest uses *functional approximation NNs* to model the variation of the system around the operating point.

(Gururajan et al., 2013) designed and evaluated two distinct *NN*-based approaches addressing *AR* solutions to failures on the airspeed sensor for a jet-powered research *Unmanned Air Vehicles (UAV)* for potential use in a *Sensor Failure Accommodation* (*SFA*) scheme. The first approach was based on a *generic MLP* with a *sigmoidal activation function* while the second approach was based on the application of the *Extended Minimal Resource Allocating Network (EMRAN).* The *NN of Monitoring Aids (NNOMA),* system is applied to the *CM* and *SeV* of *multi-purpose reactor* (*RSG-GAS*) in *Indonesia*. The *Feed Forward Neural Network (FFNN),* in *AA mode* learns *reactor's* normal operational data, and models the reactor dynamics during the initial learning *(Nabeshima, 2005).*

II.4.4 - Accommodation

FAc has been addressed in the literature considering many different control objectives and using many different solution techniques. In the model matching techniques, the goal of the accommodation is defined in terms of similarity between the closed-loop system matrices of the *accommodated* and the nominal (with optimal behavior) systems.

Strict requirements on reliability and safety of certain engineering systems make it necessary to develop means that guarantee fault tolerance of these systems. The existing approaches assume operative detection and localization of faults and, possibly, estimation of their magnitude followed by subsequent system recon figuration or formation of special control that makes it possible to preserve important characteristics of the system in the presence of the faults (perhaps, at the expense of worsening secondary characteristics). The latter approach is called *FAc* *(Zhirabok, Shumsky, 2008). FAc* system objective is to support an operator's decision making and keep the process running safely and optimally.

FAc is performed in situations where parameters or constraint structures change due to a fault. Once a fault is detected and diagnosed in the *monitoring* stage, the *FAc substitutes erroneous* measurement from the failed component reading (*i.e., sensor*, *detector*) with an alternative reliable estimate of the *true signal values (Samy et al., 2011; Gururajan et al., 2013) e.g.,* delivered by *NN estimate (Hussain et al., 2015).* The need for *FAc* becomes even more critical when the measurements from a failed sensor are used in the *control loop.* However, the *controller* will *switch* to the *estimated value* to *continue* the *system operation*. Therefore, delayed parameter estimation delays the *FAc* and can seriously undermine the efficiency of the supervision process.

In an *SFDIA* scheme, once a sensor fault is detected and identified, the faulty sensor output disconnected (*isolate* the *false information*) and it is replaced with a reliable estimate *(Hussain et al., 2015).* On other side, *FAc* is a common approach to achieve fault tolerance. In contrast to control reconfiguration, accommodation is limited to internal controller changes. The sets of signals manipulated and measured by the controller are fixed, which means that the loop cannot be restructured *(Blanke et al., 2006).* The *FAc* task is responsible for providing an alternative estimate instead of the measurements from the failed sensor *(Gururajan et al., 2013). FAc* is achieved by *substituting* (*replacing) erroneous measurements* (*e.g.,* faulty sensor reading) by an *accurate estimate* of the *true signal values (Blanke et al., 2001; Baraldi et al., 2010), e.g.,* delivered by *NN estimate (Böhme et al., 1999a; Hussain et al., 2015). FAc* is done either through *SR* and/or *FTC*. In *FTC*, the objective is to control the system under actual constraints. In *SR*, part of the actual faulty system is replaced by another one, *e.g.,* selection of alternative input and output for a controller. Once the fault magnitude is estimated, then the next step concerns accommodation of the identified fault by suitably changing the control laws, if possible *(Blanke et al., 2003).* Therefore, in *FAc*, the *FDI* module must detect and isolate the faults, as well as estimate them, in order to determine the appropriate control law for the *FTC* algorithm *(Morse, Ossman, 1990). FAc* for *FTC* is a change in controller parameters or structure to avoid the consequences of a fault. The *input-output* between controller and plant is *unchanged*. The original control objective is achieved although performance may degrade *(Blanke et al., 2001).* Most of the *FA* methods presented in the literature assume the existence of a perfect *FDD* module providing a precise estimation of the post-faulty behavior. However, for the real successful application of an overall *AFTC* design, the effects of imprecisions in the *FDD* module on the control loop have to be taken into account. The survey paper *(Blanke et al., 2001)* gives the state of the art in the field of *FTC*, and advances are reported in *(Blanke et al., 2003).*

There are two conceptually recognized approaches to the *FAc* problems: *HR* and *AR* *(Samy et al., 2010).* Traditionally, *FDe* and *FAc* are accomplished via *HR* where identical sensors are used to measure the same parameter, and on a voting-scheme, *FD* and *FAc* can be used *(Napolitano et al., 1995).* For *SFA* purposes, most of today's *high-performance military aircraft* as well as *commercial jetliners* implement a *HR* in their sensor capabilities *(Napolitano et al., 2000).* In this case, if the signal from one sensor differs significantly from the remaining two sensors, the sensor is declared as faulty. *SFA* is achieved by replacing the *faulty sensor* with one of the two *remaining sensors* (Hussain et al., 2015). For the reason of implication of *HR*, over the *past two decades AR* has become a more appealing approach for *FA*. However, when reduced *complexity*, lower *cost*, and *weight* optimization are of concern, an *analytical* sensor *redundancy* approach is more appealing (Napolitano et al., 2000). At present, different approaches of *FAc* have been reported: there exist several variants of solving the accommodation problems, including *optimal control methods* (Staroswiecki et al., 2006), *H∝ optimization* (Weng et al., 2006), *reference model tracking* (Staroswiecki, 2005), and *adaptive control* (Jiang et al., 2003b; Bodson, Groszkiewicz, 1997; Tao et al., 2004), *Eigen structure assignment* (Jiang 1994), *pseudo-inverse* (Gao, Antsaklis, 1991) *Multiple Model (MuM)* (Boškovic, Mehra, 2002), *compensation via additive input design* (Noura et al., 2000) and *integrated diagnostics* and *control* (Mhaskar et al., 2006; Zhang et al., 2009). For a survey of recent development see (Blanke et al., 2006; Zhang, Jiang, 2008), and the references therein.

II.4.4.1 - Fault Detection and Accommodation

Since the system control laws, such as for *NPs* and *aircraft*, require sensor feedback to set the current dynamic state, even slight sensor inaccuracies, if left undetected and unaccommodated for, can lead to closed-loop instability and/or performance deterioration. So, reliable *SFDA* schemes are particularly important and becomes even more critical when the measurements of a failed sensor are used in the feed-back of a control system (Samy et al., 2010). A *block diagram* of the *Fault Detection and Accommodation (FDA)* scheme for a *system* is presented on *Figure II.29*.

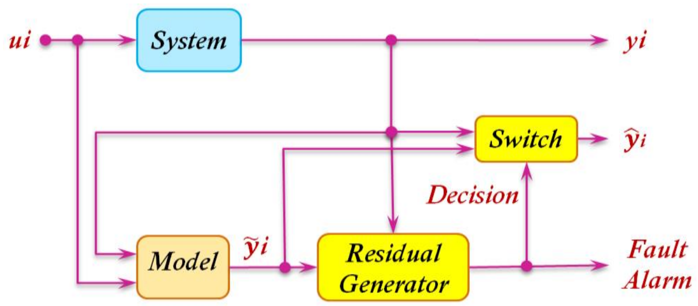


Figure II.29 - NN-SFDA outline for a fault in system.

As an alternative to traditional model-based *SFDA* schemes which rely on an analytic *MM* of the real system, *NN-based SFDA* schemes have received an overwhelming amount of research interest over the past decades. They have been successfully designed and tested on a variety of engineering systems (Blanke et al., 2003; Samy et al., 2008; Samy et al., 2010).

Over the past *decades* many *SFDA* publications have targeted fixed *model-based* approaches, with *parameter estimation* and *observer-based* methods being the most popular. A well-known technique for such sensor *FDA* problem involving *AR* is a special designed *KF* which has been used to detect and accommodate the sensor failures in the jet engine control. The *EKF-SFDA* seems to be robust to small and large amounts of parameter uncertainties. It is also robust to small modeling errors in the system and measurement noise matrices (*Q*, *R*) (Samy et al., 2010).In an attempt to widen the scope of *SFDA* schemes (Samy et al., 2008) designed and applied *EMRAN RBF* to a *NL UAV model*. This *NN* had proved a *good generalization ability* and *fast performance* (Li et al., 2000). (Samy et al., 2010) proposed two schemes based on a *NN* and the an *Extended Kalman Filter (EKF)* respectively for *SFDA* and they compared both approaches in terms of *execution time*, *robustness* to poorly *modelled dynamics* and *sensitivity* to different fault types.

II.4.4.2 - Fault Detection, Identification/Isolation and Accommodation

The *SFDIA* is an important area of research in the safety critical systems domain *(Hussain et al., 2015). SFDIA* schemes are particularly important when failed sensor measurements are used in the feedback loop of an aircraft's control laws. This could result in closed loop instability, possibly leading to unrecoverable flight conditions if the failure is not detected and accommodate for *(Napolitano et al., 2000; Samy et al., 2008).* The *FDIA* scheme must *detect* and identify any faulty sensor and *replace* it with a reliable estimate *(Hussain et al., 2013).*

Usually, the *SFDIA* scheme *(Napolitano et al., 1999)* can be divided into three distinct and sequential tasks: (*a*) *sensor Fault Detection* and *identification/isolation (SFDI),* which monitors the degree of deterioration in the accuracy of the sensors; (*b*) *validate* the sensor measurements *(SeV)* by *reconstructing* the correct values of the faulty signals (*i.e.,* replaces the faulty sensor with an appropriate estimation) *(Baraldi et al., 2010).*

There are *two* conceptually different *approaches* to the *FDIA* and *SFDIA* problems: *physical* and *Analytical Redundancy (AR)*. Traditionally, *FDIA* is achieved through high levels of *HR*. This is still the state-of-the-art practice in the aircraft manufacturing industry *(Samy et al., 2008; Zhang, Jiang, 2008; Goupil, 2011).* For example, Airbus A320/330/340/380 has triple or quadruple *HR* such as actuation, sensor and flight control computer systems *(Goupil, 2011)* in order to achieve the level of reliability necessary for the aircraft certification. Typical *SFDIA* techniques based on *HR* include voting and mid-value selection. In *HR* for *SFDIA*, identical sensors are used to measure the same parameter *(Hussain et al., 2013).* In *HR* for *SFDIA*, identical sensors are used to measure the same parameter; and fault tolerance is achieved based on a voting scheme *(Willsky, 1976).* For example, in a system with three redundant sensors, if one of the redundant signals differs significantly from the other two, the differing signal is eliminated. However, *HR* has serious cost, power and weight implications, especially for small aircraft's like UAVs. Due to these implications (disadvantages) of *HR*, *AR* has become an alternative and a far more appealing approach for *FDIA, particularly SFDIA (Isermann, Ballé, 1997). AR* uses a model of the monitored system to generate signals that would otherwise be generated by *redundant hardware*. In its simplest form, the difference between the model estimate and the measured reading is used to generate an error *residual*. This *residual* is then monitored to detect and identify faults *(Samy et al., 2011).* At nominal conditions, these signals follow some known patterns with a certain degree of uncertainty due to system and measurement noises. However, when faults occur, the observable outputs deviate from the predicted values calculated on-line or off-line from estimation. A sensor failure can be declared when the associated *residual* exceeds, for a single or for multiple time instants, a certain numerical *threshold*. Over the past *decades* many *SFDA* publications have targeted fixed *model-based* approaches, with *MM-based* methods being the most popular *(Isermann, 1997).* While proving to be successful they are usually *limited* to *linear time-invariant systems* (*LTISs*). On other side, *SFDA* can be developed with operational data without the need of a detailed model of the system. *(Neppach, Casdorph, 1995)* have presented a new *NN*-based scheme for the problem of *SFDIA* in a system without redundancy.

II.4.5 - Reconciliation

The underlying idea in *Data Reconciliation (DR)* is to formulate the process model as a set of constraints (mass and energy balance, some constitutive equations). All measurements are corrected in such a way that reconciled values do not violate the constraints. Corrections are minimized in the least square sense, and the measurement accuracy is taken into account by using the measurement covariance matrix as a weight for the measurement corrections. Sensitivity analysis can be performed and is the basis for the analysis of error propagation in the measurement system *(Heyen et al., 1996).* With this technique, variations of some state variables can be linked to deviations in any measurement.

A drawback of *DR* is the presence of a gross process fault (*e.g.,* a leak): since the basic assumption of *DR* is the correctness of the model, it is efficient to detect and correct failing sensors, but it may be less adequate to detect process faults. In this case, the DR procedure will tend to modify correct measurements while in fact there is a mismatch between the model and the actual process.

II.4.6 - Reconstruction

Detecting anomalies in sensors and *reconstructing* the correct values of the measured signals is of paramount importance for the safe and reliable operation of *NPPs (Baraldi et al., 2011b).* Fault *reconstruction* consists to estimate the fault-free values *(Yoo et al., 2006).* An effective scheme of *signal reconstruction* must be capable *providing* a *good estimate* of the true value of the signal by correlating the information coming from the non-faulty signals in the models of the ensemble plants. Within the proposed approach, a faulty sensor sends a faulty signal in input to the *PCA* models which include that signal.

The main objective of*(Baraldi et al., 2010)* work was to devise an *OLM* scheme to reduce the effects of sensor faults on the process control, by *detecting* the *faults* and then, *reconstructing* the correct *signal* values. *(Böhme et al., 1999a)* investigated the potential of *two* different *NN* approaches, *AANN* and *Kohonen's Maps*, for signal *FDe* and *reconstruction* using real data. *AANN* is a five-layer, with a global feedback loop and two different training methodologies. *Kohonen's Maps* is used to learn the structure of the data.
Authors demonstrate the accuracy of *two different NN*-based methods for signal *FDe* and *reconstruction*. It is established that *both methods* are able to *reconstruct* single soft failure as well as two consecutive faults. But their *reconstruction* quality becomes poorer if more faults occur consecutively.
(Baraldi et al., 2011b) addresses the problem of *reconstructing* the correct *signal* values measured by *faulty sensors* in *NPPs* by using *AANN* to effectively handle the dimensionality of the problem due to the large number of sensors.

Concerning the development of a *SeV* and *reconstruction* model, a common *approach* is that of using *AA* models *(Hoffmann, 2006; Roverso et al., 2007).* The practical problem, however, is that a single *AA* model cannot handle the *multiplicity* of the *measured signals* on a real plant *(Fantoni et al., 2003; Baraldi et al., 2008a).* A possible way to overtake this *limitation* is to subdivide the signals into small overlapping groups, develop an ensemble of models, one for each group, and finally, combine their outcomes. Key to build the ensemble is the *diversity* of the individual models. The groups thereby created are used to develop a corresponding number of *SeV* and *reconstruction PCA* models *(Scholkopf et al., 1999; Jolliffe, 2002).* To improve the *accuracy* of the *reconstruction*, *past signal* measurements are used as further input to the models and the *reconstruction* of the faulty signals is iterated until satisfactory convergence.

Auto-associative regression models can be used for the signal *reconstruction* task but in real applications the number of sensors signals may be too large to be handled effectively by one single model. In these cases, one may resort to an ensemble of reconstruction models, each one handles a small group of sensor signals; the outcomes of the individual models are then combined to produce the final reconstruction. In *(Baraldi et al., 2011b),* three methods for aggregating the outcomes of a feature-randomized ensemble of *PCA*-based regression models are analyzed and applied to two case studies concerning the reconstruction of a set of signals monitored at a *Finnish nuclear PWR* and a set of simulated signals of the *Swedish Forsmark*-3 *BWR*. Based on the insights gained, two novel aggregation procedures are developed for *optimal signal reconstruction*.
Usually, *reconstructing signals* in realistic applications meets the constraint of the very large number of measured signals which cannot be handled effectively by a single reconstruction model *(Roverso et al., 2007; Baraldi et al.,*

2008a). This problem is tackled by resorting to an ensemble-based signal reconstruction procedure. The ensemble approach is founded on the subdivision of the set of sensor signals into small overlapping groups; a reconstruction model is developed for each group of signals and the outcomes of the individual models are eventually aggregated to generate the *reconstructed signal* (Gola et al., 2008; Baraldi et al., 2008b) (Figure II.30).

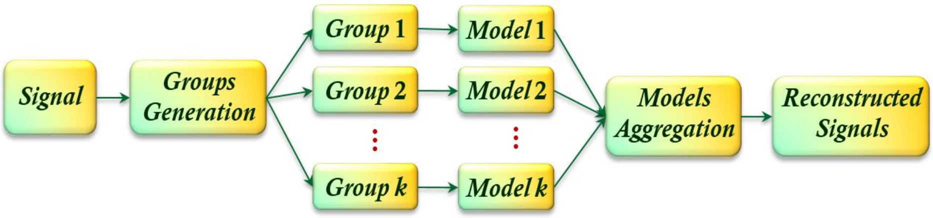


Figure II.30 - Multi-ensemble approach to signal reconstruction.

The set of signals is first subdivided into small, overlapping groups, made diverse by randomly sampling the signals according to the *RFSE* procedure. Then, one *PCA*-based reconstruction model is developed using the signals of each group. Finally, the outcomes of the models are aggregated to provide the ensemble reconstruction (Baraldi et al., 2011a).

The mathematical background and other details of the *FDIR* technique are given in (Desai, Ray, 1984). The sensor calibration and measurement estimation technique is also a sequential procedure which is performed on-line in the framework of the aforesaid *FDIR* technique.

FDIR is an important and challenging problem in many disciplines such as *chemical engineering* (Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c), *nuclear engineering* (Kim, Bartlett, 1996) *aerospace engineering* (Favre, 1994), and *automotive systems* (Isermann, 2002).

The *FDIR* technique used in the *FTo* system is a sequential *DM* procedure that systematically seeks out the largest consistent subset from a set of redundant measurements where the consistencies among individual measurements of a given process variable are determined on the basis of allowable errors.

II.4.7 - Reconfiguration

After the *FDe*, it is the task of the *reconfiguration* to switch to the *standby function module* and to remove the faulty one (*Figure II.31*). These *modules* can be *hardware components* or *software parts*, either *identical* or *diverse* (Isermann, 2006).

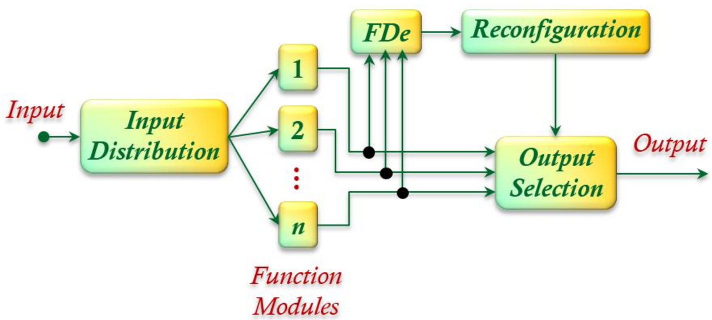


Figure II.31 - Basic scheme of FTo system with parallel function modules as redundancy.

The *reconfiguration* is a change in input-output between the controller and the plant through change of controller structure and parameters. The original control objective is achieved although performance may degrade (Blanke et al., 2001). The *reconfiguration* step involves *changing* the *controller* in response to the detected faults to ensure a safe and satisfactory operation of the system (Hwang et al., 2010).

The *reconfiguration* is the stage in which the entity (operator, engineer, controller, *etc.*) responsible of the proper operating of the system must remedy the fault that has arisen *(Harris, 1991).* This step can be seen as a return to the nominal operating conditions of the process which is digested according to the types of the encountered problems. It includes corrective actions on physical process components and / or adjustments to process control settings.
The *reconfiguration* that acts on the preceded by adapting the hardware configuration to the situation, as well as on the control system by changing the control law *(Kempowsky, 2004).*

There are various *methods* of *reconfiguration* control, such as those based on *on-line learning* or *system identification*. *(Hwang et al., 2010)* focused on *reconfiguration* control methods based on *FDI* techniques which are classified as the multiple-model approach and the adaptive control approach.

The difference between *accommodation* and *reconfiguration* whether input-output between controller and plant is changed. Reconfiguration implies use of different Input/Output (*I/O*) relations between the controller and the system. Switch of the system to a different internal structure, to change its mode of operation, is an example of such *I/O* switching. Accommodation does not use such means.
Both *FAc* and *SR* strategies may need new control laws in response to faults. They also have to manage transient behavior, which result from the change of control law or change of the constraints' structure. Two different strategies can be in turn distinguished in *AFTC*. In the so-called *FAc* approaches, new tuning parameters for the controller are calculated according to the *FDD* estimations. This strategy requires that the *FDD* module provides a precise estimation of the fault. On the other hand, in the *SR* strategy, the connections between the controller and the system are modified to compensate the fault (for instance, use of an additional sensor to substitute a broken one). This strategy requires only *FIso* (identification of the faulty component), but not fault (size) estimation. The problem is that *HR* of components is required.

II.4.8 - Fault Removal

The *fault removal technique* is mainly used to reduce the number of faults which are present in the system. During development and operational phases of the system; fault removal is performed. Fault removal during development phase is completed in three steps: *verification*, *diagnosis* and *Correction*.

Verification is the process of checking whether the system satisfies the pre-specified conditions. If it so happens, the next step is the *diagnosing* the faults that prevented the verification conditions from being fulfilled and then performing the necessary *corrections*. During operational phase, fault removal is performed in following two steps: *corrective* and *preventive maintenance*.

During operation phase, the *corrective maintenance* is performed to remove faults that have produced one or more errors and have been reported. In case of *preventive maintenance*, some adjustments are made or parts which may undergo to be faulty during normal operation are replaced before occurring the system failure. In addition to this, preventive maintenance is the achievement to avoid high cost of replacement or avoid damages of the surrounding of the system components. It is to be mentioned that the corrective and preventive forms of fault removal technique are applied to fault tolerant systems as well as non-fault tolerant systems that can be maintained without interrupting service delivery or during service outage.

II.4.9 - Decision-Aided

Seen the complexity and size of current plant systems, operators and decision makers are forced to manipulate considerable information of monitoring and control an increasing number of variables and parameters. Furthermore, this information received as measurements are susceptible to error and uncertainties making the job of operators more and more difficult. Therefore, the operators made mostly call to an outside help to a *DM*. In this situation, the operators need indicators and tools for *FM* and *DM* to *perform*, *validate*, *justify*, *evaluate* or *correct* important *decisions* which should be taken. This is made according to criteria more complex and interdependent. Therefore, the design of a *supervision system* associated to an assistant decision tool seems necessary *(Olivier-Maget, 2007).* This allows the operator to take advantage of the computer component and to cooperate together to carry out a better supervision of changes and anomalies. This offers also the possibility of increasing accuracy and speed of decisions and makes them more effective. For example, the general structure of a model-based *FDi* system comprising residual generation, residual evaluation and decision making (*Figure II.32*). The residuals are evaluated for the likelihood of faults, and a decision rule is then applied to determine if any faults have occurred.

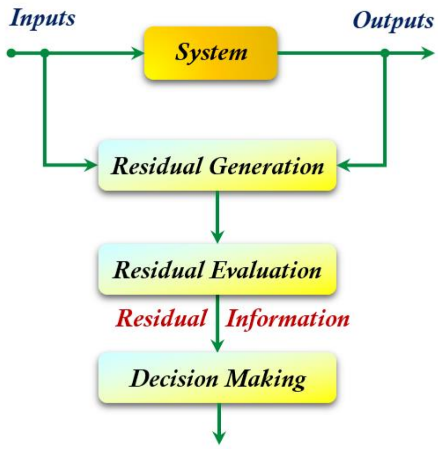


Figure II.32 – Emplacement of decision making at supervision system.

DM is a reasoning method and a complex cognitive processes phenomenon being able to learn on rational and\or irrational arguments. It is based on the knowledge and the experiment of the *decision-makers*, as well as on the historic analysis. It is a control phase *(Verron, 2007)* activated when we feel a need to act without knowing how to steer a given situation. It implies the apprehension of the risk and the commitment of the responsibility. It is the activity of taking support on models clearly explicit and completely formalized, and helps to obtain answers to the asked questions by a speaker in a process of decision.

DM exploits the progress of the data processing, to help a *decision-maker* to analyze a problem appeared during operation and to show him how to find final solutions for abnormal and emergency states by selecting, by mean of some procedures, *e.g., automatic*, a manner of action among several alternative and arrangement scenarios and to put it back to the operator to help him in processing correctly the situation after the apparition of the fault.

The decision determines the state to be reached for the return to normal operation and the sequence of corrective actions to achieve to arrive at this state *(Kempowsky, 2004).*

DM can be an action or an opinion of choice, but decision without action remains a simple hypothesis without suite. So, we have to differentiate between *find solutions* to a problem and resolve it (eliminate definitively the problem). The *DM* can be done by determinist or probabilistic approaches *(Zhang, 2010).*

The progress of the computing and the *AI* have been integrated in the *Aided Decision System (ADS*), domain aiming to design computer tools and to exploit it in *ADS*'s started (*e.g., software - expert*). *Computing decision* indicates means, tools and methods which allow collecting, strengthen, model and restore data, material or immaterial, of a system to offer a help to the decision and allow the decision makers of the company strategy to have a general view of the processed activity.

There are three decision types: *(a) non-structured decision* - the administrator emits a judgment, an evaluation and a point of view in front of a problem without ready-made answer or pre-established procedure; *b) structured decision* - is a repetitive and routine activity accompanying by a defined procedure, *(c) semi-structured decision* - contains a part of the problem which can be only adjusted with a predefined procedure.

There are four *decision modes*: (*a*) *autocratic* - the responsible collects and analyses data, arbitrates and decide alone; (*b*) *consultative* - decision maker, before cutting, asks for opinions and for the suggestions of the co-workers concerned by the question; (*c*) *concerted* - the decision maker puts its co-workers in the fact of the problem and invites them to elaborate possible solutions; (*d*) *co-decision-making* - the decision maker and concerned co-workers analyze problem in common and discuss to agree on a proposition to be taken. The choice of such or such mode depends of: the nature of the problem; constraints of time and the style of the practiced management.

To perform *DM,* several steps are needed: (*a*) *Perception of the key elements of the situation* to detect the symptoms of the situation requiring an intervention, and to formulate correctly the objective to achieve; (*b*) *Identification* of the problem by looking for, study and analyze available means. (*c*) *Elaboration of so*lutions by listing all the possible solutions and analyzing advantages and drawbacks of every solution towards reserved criteria; (*d*) *Choice of a solution* by choosing between various possible options and to elaborate an action plan allowing the implementation of the decision. (*e*) *Implementation* of the decision by communicating retained solutions, looking for the feed-back of the implied partners and realizing actions for implementing the decision; (*f*) *control* by checking actions, analyzing gaps and comparing obtained results with regard to the defined goal.
When decision is difficult to take, there are several steps one can take to ensure the best possible solutions will be decided. These steps are put into seven effective ways to go about this *DM* process: (*a*) *outline your goal* and *outcome*. This will enable decision makers to see exactly what they are trying to accomplish and keep them on a specific path; (*b*) *gather data*. This will help *decision makers* to have actual evidence and help them to come up with a solution; (*c*) *brainstorm to develop alternatives*. Coming up with more than one solution allows you to see which one can actually work; (*d*) *decision making*. Once each solution is analyzed, you should pick the one that everyone can agree with. (*e) immediately take action*. Once the decision is picked, we should implement it right manner; *f) learns from, and reflects on the DM*. This step allows you to see what you did right and wrong when coming up, and putting the decision to use. Finally, these decision steps are summarized on the following *Figure II.33. (Pijanowski, 2009)* developed eight stages of *DM* based on the work of *James Rest*.
Finally, these stages can be summarized in two main phases: (*a*) *problem finding*: the *decision-maker* determines which to be confronted; (*b*) *problem-solving*: it is the most studied phase which consists to answer the first formulated problem. It is possible that in this stage, the *decision-maker* will be obligated to reformulate his initial problem. In turn, the *problem-solving* phase is decomposed into several stages and notably: (*i*) the collection of information; (*ii*) the analysis of this information and the creation of potential solutions; and (*iii*) the *DM* which follows on this analysis, consists in choosing and so to give up the other possibilities.

As soon as the software on a *PC* can help a manager to make a *decision*, this program will be certainly called *ADS.* After data are analyzed by *FM* system, the *ADS* consists to collect passively these data, to analyze the coherence of data measures and to organize them in an effective way to allow the selection of a type of action among different alternatives as a reliable suggestion for *DM* stage. To make a good decision, one usually based on the quality of data and the capacity to be reviewed and analyzed to find tendencies which lead to create solutions and strategies of the *decision making*. So, the *ADS* offer the possibility of increasing precision, accuracy and speed of the decisions that the administrators seek to make them more effective.

Figure II.33 - Main steps of decision.

Several conditions are ideally necessary for *ADS* such as good understanding of problems and context; a complete vision on data and information; the taking into consideration of all the possible solutions; caution in the future predictions and results, including an evaluation of risks and access to adapted and modern tools of *ADS*. So, *ADS* took increasing places in certain processes of decision so much so that it is often replaced the man component by automatic processes.
The *ADS* systems can be classified into three main axes: the *systems of information and analysis* (*systems of documentation*, *data bases*, *data analysis*, *simulations*, some *ES*s, *etc.);* the *ADS* systems (*ESs*, *choice support software*, *etc.);* and the *communication* and *cooperation systems*.
Furthermore, the *ADS* works can be subdivided into *three* main *families* corresponding to *three* different *methods (Roy, 1990).* (*a*) The *first* way aims to search the better decision to reach an optimal solution. So, the analysts using this method formulate problem and use operational research to resolve it. (*b*) The *second* way consists to design a set of rules, constituting a set of requirements. It characterizes rational behavior in a decision. The analyst conceives a reasonable set of hypothesizes so that the decision-maker can get adequate conclusions concerning its decision. Among the works using this method, the utility theory hoped from and multi attribute of *(Keeney, Raïffa, 1993).* (*c*) The *third* way has for object to supply, to the decision-maker, advices and recommendations. It does not try to give an optimal decision because of conflicts and alterations which intervene during the progress of the procedure of *decision*. But it supplies rather an appropriate decision resulting from a compromise action. Furthermore, it allows involving the *decision-maker* in the construction phase of the model so, that it can integrate it into his preferences. By opposition in the first two big families, this third does not consider the *decision-maker* as rational. More details concerning this method as well as the criticisms of first two approaches are available in *(Moisdon, 1986)*.
On other side, in *consultant system*, the user supplies information about the state of the system and in turns it receives an advice. In *semi-active system*, the call to the system is made automatically. It is a watch-dog system and automatic reminder system which oversees the user attitude. It allows avoiding redundant investigations and prescription errors. Alarm system allows taking attention on the situation of the system modification, and indicates abnormal parameter value change. An active system of *ADS* shows explicitly solutions based on data. They start automatically and can make decisions without intervention of the operator. Although there are numerous systems which are able of being active, numerous organizations would be difficult to put all their faith in a computer model without any human intervention.

With the proliferation of plants in different field of industry, during the last years there is a fast increase of the information collection capacities. This allows weighing down the analysis and the check of the validity of this information. So, in this case we need of the so-called extraction tools of information which can play an important role in various domains such as the analysis of complex systems. These tools influence the analysis quality and, as a consequence, influence enormously the decision process as shown on *Figure II.34.*

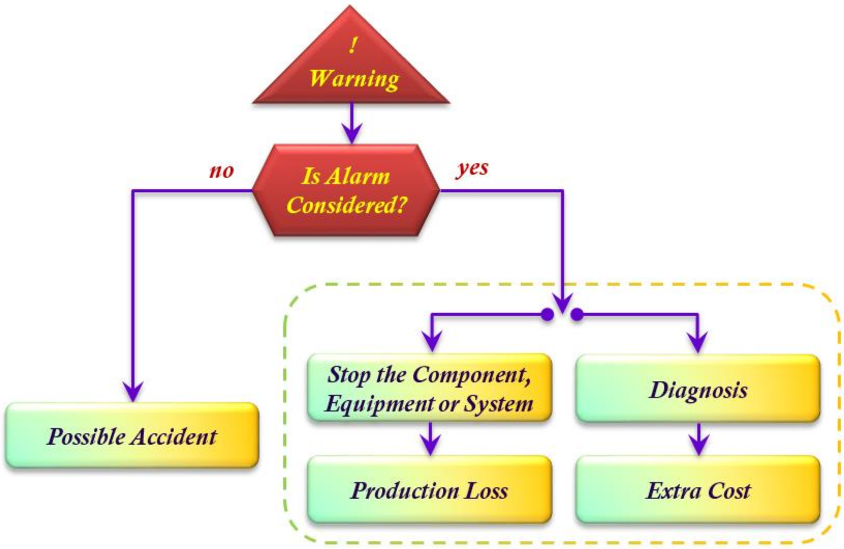


Figure II.34 - Impact of decision making on the plant.

II.5 - Conclusion

The objective of this chapter was to provide a description of the *FS* and its constituents which are mainly the *FM* and *FC*. This description included a presentation of the most important terminology and keyword, commonly used in *FS* domain, to prevent ambiguity which can be meet in the literature. Among this terminology we find particularly the fault which is overviewed. In this chapter, we illustrated that *FM* of industrial process, systems and equipment is done through two basic functions; *FDe* and *FDi*. *FDe* has the role of reporting any situation other than a nominal situation. In other words, anything that is not normal must be classified as abnormal. Then the *FDi* function must locate the failing organ and identify the causes that caused these failure situations. This operation is often conducted by an expert and in some cases requires extensive knowledge of the equipment. Furthermore, a detail on *FDe* and *FDi* is given including definitions, composition, features and some applications. *FC* is also described in this chapter by giving the definition of common functions used in this field.

CHAPTER III

Fault Monitoring Methods

The monitoring is the process of identifying (detecting) deviations from normal or expected operation (faults) and give necessary information (diagnosing) on the problem. The monitoring process relies on an explicit model of the normal system behavior or phenomenologist (function), its structure, and/or its known faults.

The basic aim of this chapter is to give a broad review to the state of the art of the most common (current) approaches of detection, diagnosis and accommodation of industrial plants, particularly NPPs. Then, to present a comparative analysis of these techniques. Most of these methods are based on historical data and data retrieved online during the operation of the monitored system. They are used to build a behavioral model of the process to identify, as early as possible, abnormal situations resulting from malfunctions and failures, to help finally the human operator in his decision making.

These diagnostic techniques are presented in this Chapter, technical details of their implementation are provided, the advantages and drawbacks of every technique are outlined, examples from recent research work of expert diagnostic practice in industry are presented.

III.1 - Introduction

A great variety of *methods* have been intensively studied, proposed, developed and presented over the recent years to improve the capabilities of *CM* in different domains and applications such as *petrochemical processes*, *air transport* (*aviation*), *chemical reactors* and *NPs* and most of these approaches are applicable to steady-state processes. So, the sample group of monitoring methods is considerable, and each of these competing methodologies has their own distinct *advantages* and *disadvantages* *(Olivier-Maget, 2007).* Therefore, the choice of the appropriate approach is related to the knowledge that one wishes to acquire on the system, but also to the nature of this system.

CM approaches have relied on *analyses* of specific *measurements* and *aspects* of the *operation* (*e.g.,* vibration analysis, strain measurement, thermography and acoustic emissions). Generally, *CM* systems are *based* on *measurements of process variables* (acquired from industrial equipment) and *variable observed by humans* (operators). The most successful reasoning strategies employing models *require* not only the *model* of the *observed process* but also a *model* of the *process* running in *normal conditions* and the set of *models* of the *faulty process* - as many as the number of faults to be detected. Common ways of performing *CM* include acoustic measurement-based methods, electrical effects monitoring, power quality and temperature monitoring, oil debris monitoring, vibration analysis *(Dias et al., 2016; Huang et al., 2017),* physics based data analytics *(Luo, 2017), etc*.

The *FDD* methods have been reviewed in a number and survey papers *(Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c; Dochain et al., 2006)* and books *(Isermann, 2006; Witczak, 2007).* Furthermore, an extensive comparison of the various methods can be found in *(Wang, Man, 2014; Yan et al., 2014).*

III.2 - Classification of Methods

Since the beginning of 1970, worldwide attention to research in *FM* has been increasing, both in theory and application; a strong impulse comes from the area of modern control theory, which has brought powerful techniques that have become feasible thanks to the progress of *computer technology*. The contribution of these *FM* approaches is indisputable. It is more essential to set up such monitoring systems, to require detailed knowledge of the installation: knowledge of its normal behavior but also and especially its abnormal behavior. So, these systems require, for their good progress, information about non-measured parameters.

A considerable number of approaches for *FM* have been developed for *monitoring* of engineering systems *(Crowther et al., 1998).* The *FDD* methods proposed by *(Katipamula, Brambley, 2005)* shows the fundamental and most common *FDD* approaches, and the advantages verses the challenges of each one of them. At present, several classifications of these methods have been suggested and studied in the literature in different ways *(Zhang, Jiang, 2008; Ma, 2015).*

One can distinguish *two main categories* of methods; based on *applications* and based on *dependence on the system* *(Zhang, Jiang, 2008).* The *first* category is influenced by the context and the particular *domain of application* (area of consideration) in every community and therefore not homogeneous *(Olivier-Maget, 2007; Yu et al., 2014).* The *second* category is influenced by the way and form of the used *process knowledge* *(Dash, Venkatasubramanian, 2000).* Particularly, these methods are classified as ones which use *process-model information*, and ones which rely on *process-history-based knowledge*. The *former* rely on *deep*, *causal* or *model-based knowledge* while the *latter* rely on knowledge extracted from *past experience* with the process otherwise known as *shallow*, *complied*, *evidential* or *process history-based* *(Dash, Venkatasubramanian, 2000).*

Among these classifications of methods, we also distinguish mainly: *model-based/model-free* known also by *deepened/non-deepened knowledge* (Olivier-Maget, 2007; Ma, Jiang, 2011), *Model-based/Data-based* (Zhou et al., 2003). (Venkatasubramanian et al., 2003a) classified these methods based on the form of *process knowledge* in terms of *model-based (quantitative/qualitative)* and *process history based*.
We find also in literature other classification such as *internal/external, static/dynamic* (International Atomic Energy Agency, Vienna, 2008).
However, for some monitoring techniques, the distinction between these different categories and classifications is unfounded because they use in a mixed way the parts of the classification by trying to benefit from advantages and free oneself from limitations of each of them. Therefore, it is often delicate to determine a method the most appropriated for the resolution of the *FDe* and *FDi* problem.

III.2.1 - Model-based/Model-Free Methods

At a first level, the *FM* methodology usually could be divided as it is shown on *Figure III.1,* into two major families *with model* and *without model* (Olivier-Maget, 2007; Ma, Jiang, 2011; Adouni, 2013). So, the existence of formal or *MM* of the system defines the method to be used. *First*, the methods which require a detailed knowledge on the physical system or these which use the physical system itself under *HR* form; they are methods base on *phenomenological models* are *MBTs. Second,* methods not requiring greater knowledge of the physical system, but which use a knowledge inspired from the past experiments; one distinguishes then methods *without model* or *based on behavioral models*; they are *model-free methods (MFMs).*

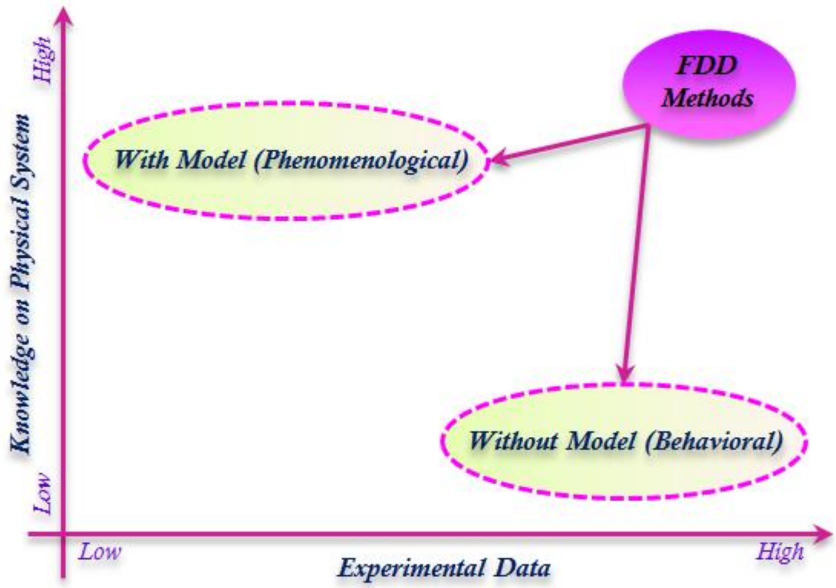


Figure III.1 - Classification of FM methods into model-based or model-free (Olivier-Maget, 2007).

In the *first category*, *HR* schemes were firstly developed to detect faults in physical components using identical hardware components. Although this method is of high reliability and can directly isolate faults, using redundant hardware, leads to congestion and increase cost and time-consuming processes.
After computer science community has developed continuously, computational techniques have become the main potential innovation in terms of software forms by exploring physical laws used in process components and knowledge-based schemes. As a result, most *HR* approaches have been substituted by *AR* schemes to tackle the aforementioned *constraints*.

The *second category* of methods is very interesting when the model of equipment or component does not exist or difficult to obtain. In this case we use the available measurements (data) and knowledge to extract information then to use statistical and *AI* tools to treat them to represent the different operation modes of the equipment.

The *difference* between these *two approaches* (*i.e., model-based* or *model-free*) lies on the way the *symptoms are generated*. The main step in all *MBTs* is the *generation of fault symptoms* by *comparing* a reference or *normal operation* model with *actual data*. In *model-free FDD,* the available behavior is translated into suitable *symptom* and reasoning strategies are applied to reach detect fault and to *FDi* decisions. Contrary to *MBTs, FMMs* have the advantages to do not need the knowledge of mathematical or structural model of the process. Only, the availability of historical data of the process is needed.

The main step in all *MBTs* is the *generation* of *fault symptoms* by *comparing* a reference or *normal operation* model with *actual data*. *MBTs all use* models developed in either *online* or *off-line mode* but the *difference* between them (*i.e., model-based* or *free model*) depends on the way that the *symptom (i.e., model) is generated.* The manner to form *MBTs* is typically grouped into *quantitative* and *qualitative models* (*Figure III.4*).
Quantitative models (*differential equations*, *state space methods*, *transfer functions*, *etc*.) are used to generally utilize results from the field of the control theory. In *qualitative models*, the relation between the variables to obtain the expected system behavior is expressed in terms of qualitative functions centered on different units in the process such as causal models and abstraction hierarchy. They are used, in particular, for large and *NL* systems. The analysis methods used in the *qualitative model* are *Fault Tree Analysis (FTA), Failure Modes and Effects Analysis (FMEA), ETA*, structure analysis, *etc*. These methods can provide an efficient solution for most *FDe* problems. But in some cases, it cannot give correct detection results since the valid process *MM* required, in this technique, is difficult to be obtained in some industrial processes.

In *FMMs,* one distinguishes different types of methods classified in different manners. *(Olivier-Maget, 2007)* classified *FMMs* based on *behavioral knowledge*, into *knowledge-based* and *data processing-based.* The *first* methods are implemented when the construction of the model is difficult or the available data and measurement on the system are not sufficient. So, the experience and acknowledge of the operator are exploited to guarantee the good operation of the process *e.g.,* the *analysis of the failing modes and their effects (MADE) fault trees (FTrs)* or *cause trees* and *ESs (Villemeur, 1988, Kempowsky, 2004).* The *latest* methods require usually a wide range of *historic data* during a step of *characteristics extraction* and then, they analyze these data by various techniques. Therefore, these data are considered as source of knowledge for the monitoring system. One distinguishes usually two types of *procedures* according if it is *statistical* or not. Therefore, these techniques are the *statistical techniques* of data (*e.g.,* the *PCA; data classification (Ribes et al., 2002; Kempowsky, 2004),* and *shape recognition);* and the *non-statistical methods* (*e.g., frequency approach (Orantes Molina, 2005), NNs*, the *tendencies qualitative analysis (Cheung, Stephanopoulos, 1990).*
(Zemouri, 2003) In his general introduction divided *model-free monitoring* technics into *two parts.* The *first one* corresponds to *statistical tools* and *SP* which are usually qualified as *low-level processing* tools, because they are in *direct contact* with the *sensor signal*, and are usually used only for the generation of alarms, without any information regarding their meaning. The *statistical tools* establish tests on the acquisition signals, tests that are only able to *ensure* the *FDe* function. The *second part* is that of so-called *high-level techniques* which are more oriented towards communication with the expert. These represent the techniques of *AI* and serve as a basic tool for *decision support*. Their response is therefore more elaborate than that of low-level techniques and they are able to *detect*, *interpret* (association with a mode) and *diagnose* failures. The author, then, proposed a *second classification* with *two parts*: *statistical tools* and *PR*. The statistical tools are able to establish tests to ensure only *FDe.* On the contrary to statistical tools, the *Knowledge-Based Technique (KBT)* are more elaborate compared to simple statistical tests and are able to detect and diagnose fault.

Further, *(Ma, Jiang, 2011)* classified *model-free methods* into *DDTs* (*multivariate*) and *SiBTs* (*univariate*) as shown by *Figure* III.2. *Data-driven FDD methods* rely on relationships between correlated measurements within a system. However, the relationships can be formulated in an implicit way by training an empirical model through analysis of fault-free training data obtained during normal operations. This empirical model is then used to estimate true values of new measurements, and faults are detected and diagnosed by evaluating the estimation residuals. *SiBTs* make *FDD* decisions by comparing features (*e.g.,* spectrum) extracted from a signal with desired normal baseline values. We not that in some references, *SiBTs* are included in *DDTs*.

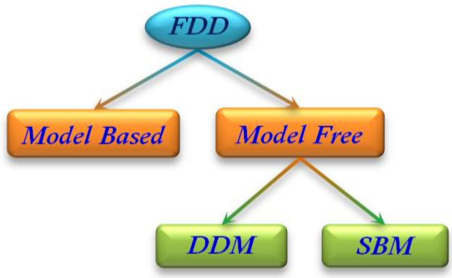


Figure III.2 - Classification of FM methods into Mathematical Model Technique (MMBTs) M, DDTs and SiBTs.

While practical applications of *MMBTs* are very limited, various *DDT*s and *SiBTs* have been extensively applied for *monitoring* key subsystems in various industrials *(Hines, Davis, 2005; Rehorn et al., 2006).*

III.2.2 - Model-based /Data-Driven Methods

According to *(Yang Qingsong, 2004; Zhang, Jiang, 2008; Mandal et al., 2017), FM* methods can be classified into *two categories* as illustrated on *Figure III.3*: *model-based* and *data based methods* also called *DDTs*, or *process history (Amann et al., 1999; Granderson et al., 2017).*

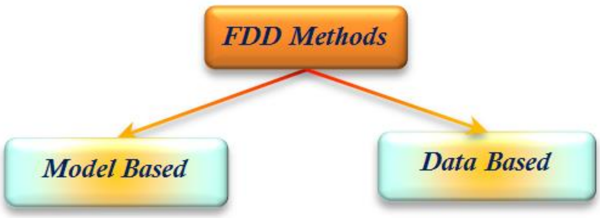


Figure III.3 - Classification of FM methods into MBTs and DDTs.

(Zhou et al., 2003) added to this classification, the *combination* of both categories. This classification is most dominant and is based on the required a priori *process knowledge,* (*i.e.,* is the set of faults and *relationships* between the *symptoms* and the *faults*) *(Yang Qingsong, 2004). (Zhang, Jiang, 2008)* divided also the *model-based* and the *data-based methods* into two groups: *quantitative* and *qualitative methods* as shown on *Figure III.4.*
*DDT*s *(Wilamowski, 2011)* need healthy and faulty data from the system which in turn requires large amounts of data transmission and computation. By contrast, in the *MMBTs (Wilamowski, 2009),* the *MM* of the system along with the sensor measurements are utilized to detect and diagnose faults. Researchers have worked on model-based *FDe* schemes, using *adaptive estimators*, *NN* based estimators *(Campa et al., 2002a; Samy et al., 2008), fuzzy observers*, *etc*.

The *MBTs* rely upon knowledge of the underlying physical processes and first principles governing the system(s) being analyzed. *Quantitative model-based approaches* which include rule-based FDD, have been extensively used in the industry.
The *process history-based* (*data-driven*) approaches do not rely upon *knowledge* of *first principles*, but may leverage some degree of engineering knowledge; they rely upon data from the system in operation. These include *statistical regression models*, *NNs*, and other methods.

III.2.2.1 - Model-Based /Data-Driven Methods/ Knowledge-Based

Based on the type of knowledge they use, *FM* methods differ and therefore we can so classify them in *MBT*s, *KBT*s and *DDTs* (Sankavaram et al., 2009) as shown on *Figure III.4*. *MBT*s are based on a *structural model* of the of the *dynamic system behavior* and on fundamental laws governing the system. They employ consistency checks between the sensed measurements and the outputs of a *MM*. The expectation is that inconsistencies are large in the presence of malfunctions and small in the presence of normal disturbances, noise and modeling errors. Model can then be *quantitative* (for example a *system of algebraic differential equations*), *qualitative* or *semi qualitative* (for example a *set of logical relations*), or also *fuzzy* (representation of the characteristics of a system by means of *fuzzy rules* which describe its behavior). *Historic DDT*s preferred when system models are not available, but instead big quantities of *historic data* of the process are then necessary. *DDT*s are preferred when the system monitoring data for nominal and degraded conditions is available. In *KBT*s *knowledge*, *competence* and *reasoning* of the *human experts* are valued in these methods. They are indeed translated into rules to resolve problem. *KBT*s use graphical models such as *dependency graphs* (*digraphs*), *Petri nets*, *multi-signal* (*multi-functional*) *flow graphs*, and *Bayesian networks (BNs)* for *FDi* knowledge representation and inference.
On the other hand, (Yu et al., 2014) have been classified *FM methods* into *three* categories: *ABTs*, *KBTs* and *DDTs*. In the *FM method classification* given by (Zhang, Jiang, 2008), the *model-quantitative-based*, *data-quantitative-based*, and the *combination* of *model-qualitative-based* and *data-qualitative-based methods* as shown in *Figure III.4*, can be seen *respectively* as *ABTs, KBTs* and *DDTs* in (Chiang et al., 2001; Ng et al., 2001) model.

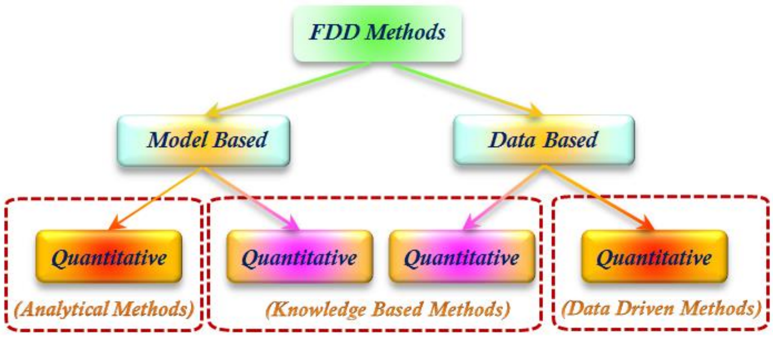


Figure III.4 – Rearrangement of Classification of FM methods given by (Zhang, Jiang, 2008) into ABTs, KBTs and DDTs.

In *quantitative* and *qualitative MBTs, AR* is used to generate *residuals* that can be used to detect faults. The *quantitative MBTs*, such as parity relations, observer-based methods and *KF*s, use *MMs* for *residual* generation, while *qualitative MBTs* use *PR* techniques for *FDe* (Venkatasubramanian et al., 2003b; Hwang et al., 2010).
The analytical model, according to (Chiang et al., 2001; Ng et al., 2001), is not adequate for large-scale *NL* and complex systems. All measures based on *DDTs*, *ABTs*, and *KBTs* have their advantages and disadvantages, so that no single approach is best for all applications. (Khalastchi, 2018) summarizes the general advantages and challenges of each type of *FDD* approaches when have applied to robotic systems.

III.2.2.2 - Model-Based / Knowledge-Based Methods / Signal-Based

FM methods can be classified into *three main categories* as shown in *Figure III.5*; *Model-based*, *Knowledge-based* and *signal-based* (Alexandru, 1998).
SiBTs depend on the analysis of measured signal without knowing the system model especially for large and/or complex. The fault can be detected by applying a simple analysis, such as the *Limit Checking* (*LC*) method, frequency analysis method, data characteristics analysis method, *etc*. or advanced technique such as, the *principal-component analysis* (*PCA*), wavelet and *PLS* analysis.

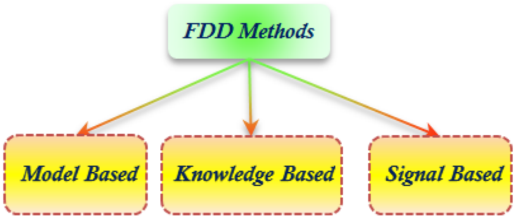


Figure III.5 - Classification of FM methods into MBTs, KBTs and SiBTs.

(Gao, 2015a, Gao, 2015b) added to the previous categorization of *FDD methods* the *hybrid FDi* and *active FDi*. Hybrid *FDi* is an integration or combination of more than one *FDi* methods. Active *FDi* is to enhance the detectability of potential faults by injecting a suitably designed input signal under test interval so that faulty modes can be distinguished from normal modes quickly and accurately.

III.2.3 - Qualitative/Quantitative

Other used depending on the knowledge and the nature of information processing, classified *FDi* methods as *quantitative based methods* and *qualitative based methods*. The precedent classification, *MBT/DDT* given by *Figure III.2* can be rearranged in a new classification based on two major categories: *quantitative* and *qualitative models* as illustrated by *Figure III.6a*. Furthermore, *(Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c; Katipamula, Brambley, 2005)* have been added to this *classification* a third category which is the *process history-based methods* as presented by *Figure III.b*. *Quantitative approaches* are mainly *analytical models* based on the *mathematical modeling methods* (*parity space*, *observers*, *parameter estimation*, *etc.).*

Figure III.6 - Classification of FM methods into: (a: left) qualitative and quantitative methods. (b: right) qualitative, quantitative and process history-based methods.

III.2.4 - Other Classifications

(Ma, 2015) proposed a more extended classification of *FDD* as five *categories* (*Figure III.7*) : *MMBTs*, *SiBTs, PR methods*, *data fusion methods*, and *DDTs*. He listed some of well-known properties of these categories and also gave some details (such as general principle, example algorithms and typical applications). The author gave also details on each category. *(Huh et al., 2019)* categorized the approaches for the *FM* into *model-based*, *signal-based*, *knowledge-based*, *hybrid-based (Benmoussa, Djezir, 2017),* and *active approaches*.
Others *classification* of *FM methods* can be made as *linear* and *NL* characteristics of systems as given by *(Ge, Fang, 1988). (Chiang et al., 2001; Ng et al., 2001)* have classified *FM methods* in *four areas*: *HR*, *plausibility tests*, *software/AR schemes* and *SP*. These methods also may be grouped under the broad headings of *ESs (Ge, Fang, 1988)* : *Qualitative reasoning (Linkens, Wang, 1994), Model-based diagnosis from an AI perspective (Leitch et al., 1993), Model-based diagnosis from control engineering (Yu et al., 1994),* and *NNs (Yu et al., 1994).*

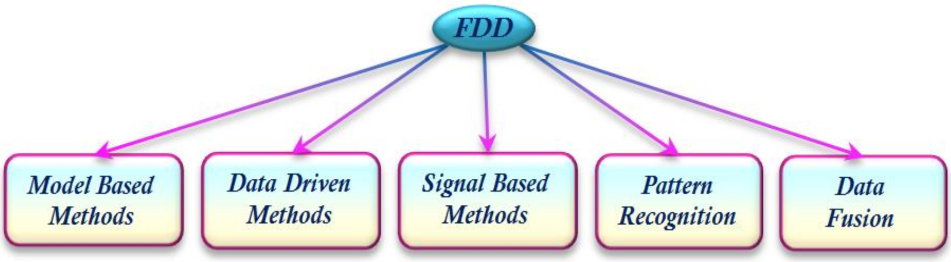


Figure III.7 - Classification of FM methods according to (Ma, 2015).

III.3 - Model-Based Methods

Model-based *FDi* was originated by *(Beard, 1971)* in order to replace *HR* by *AR*. Research into model-based monitoring was intensified during the 1980*s* and 1990*s*. Today, it is still an expanding research area with many unresolved issues. The main reference works in this field are: *(Chen, Patton, 1999).* Recently, developing and using models has become more prominent due to the complexity of modern industrial processes and the need to optimize operating conditions from both an economic and safety points of view *(Thoma, Ould Bouamama, 2000).*

A model is a simple or abstract representation (diagram, graphic representation, mathematic equations, *etc.*) of a physical system. It can be obtained by using either physical principles or systems identification techniques. Dynamic models of physical systems may be represented in different ways: logical statements *(Hayes, 1985),* mathematic equations *(Kleer, Brown, 1984), Bond Graph (BG) (Medjaher, 2005),* bloc diagram and *BG (Xia et al., 1993),* digraphs *etc*. The preference of the adequate representation of the physical system depends on the purpose of the search. The modeling is totally *dependent* on a good *a priori knowledge* of the input/output behavior of the process. A model representation of process must first be established in order to reproduce as faithfully the real behavior of the system. A model characterizes a physical system by a set of properties that facilitate its description and understanding. So, at the supervision level, any description of the process, which brings a priori knowledge on its characteristics and functionalities, constitutes a model of this process. Therefore, a precise and accurate model of the system constitutes the cornerstone of process control theory. *Model-based diagnosis* uses *knowledge* about *structure*, *function* and *behavior* and *provides* device independent *FDi* procedures. The use of *models* enables the *estimation* of *variables* and *parameters* which are *influenced* by the *fault*. In addition, *MBT*s have the *potential* of *early detection* of *slowly developing faults* in complex processes.

The models can be of different natures depending on the information available on the process. We can distinguish two main types of model approaches as shown on *Figure III.8*: *quantitative (structural, phenomenological)* models and *qualitative (behavioral*) models. The *quantitative* level reflects the connections between the different components and devices of the physical system. Whereas, *qualitative* representation is made up of so-called "*cause-and-effect*" relationships (relations between system variables).

In addition to both categories of this classification of methods*, (Olivier-Maget, 2007)* added *Fuzzy methods* as a third category. Furthermore, *(Ibarguengoytia et al., 2001)* classified the *MBTs* into two categories: *hardware* and *AR*; and *(Zemouri, 2003)* proposed a classification into *hardware* and *AR*, and *parametrical estimation*. According to the *MBTs* classification given on *Figure III.8*, it is possible to define two different formulations: *FDiso* approach*,* from the *automatic community*, based on *quantitative models*, and the *DX* approach (from the name of the *international workshop on principles of diagnosis*) of the *AI* community using *qualitative models (Kempowsky, 2004).* These methods and associated model type differ from each other not only by the knowledge available on the physical system and its faults, but also by the manner this knowledge is exploited.

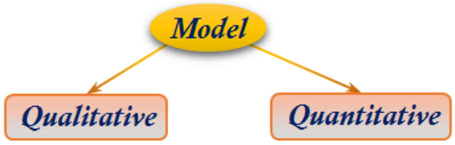


Figure III.8 - Types of Model.

Models become valuable tools for studying and making predictions only when they capture types of interactions and their magnitude. In *MBTs* for *FDD*, a *model* is used to represent the normal behavior of the system *(Ma, Jiang, 2011) to estimate* the *states* or *parameters* of the system. The *model* used in the redundancy for generating residual and then for *FM*, can be of different natures depending on the information available on the process. In *quantitative* and *qualitative MBTs,* the model is used to generate *residuals* that can be exploited to detect faults (*Figure III.9*). Residuals are used to compare measurements made on the system with information provided by the model and any difference is then traduced as synonymous of fault. Tools of *decision theory* are then used to determine if this difference is due to perturbation and noise or is the effect of system fault.

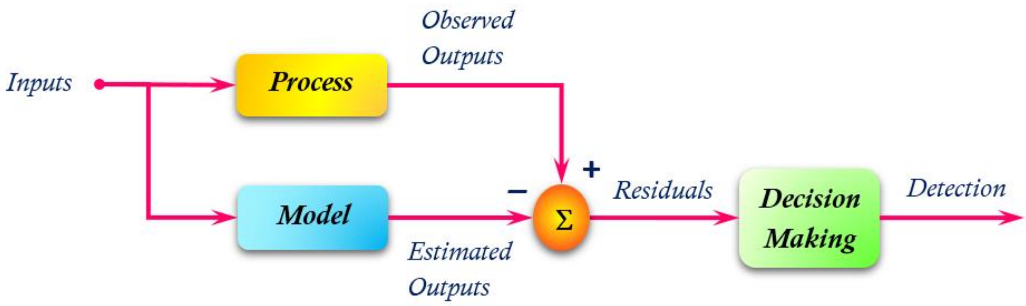


Figure III.9 - Schematic illustration of MBT for FDe.

Approaches based on *qualitative models* were widely studied in the literature *(Fussel, Isermann, 1998).* They lean on explicit models of the studied physical system. They have for principle to compare measures made on the system with information supplied by the model. *Qualitative modeling* is today most commonly referred to in the literature as *qualitative reasoning*. *Quantitative models* are more precise and specific about a system, but require a large effort in model construction. Because of this very often ecological systems remain only partially specified and one possible approach to their description and analysis comes from qualitative modeling.

Model-quantitative-based method. Model-quantitative-based method (MQnBM) is based on *quantitative* description and deeper understanding of the associated phenomena governing the physical system. It is mathematical functions expressing the input-output behavior (relationship) of the system or the sub-system (*i.e.*, device, component) built from *physic-chemical* principles and basic *laws* (*e.g., physics*, *balance equations*, *reaction*, *thermodynamics, chemical*, *hydraulic*). Therefore, these types of model are usually known as *quantitative*. *Model-Qualitative-based method (MQlBM)* are models of *analytical* (*mathematical*) type (*e.g., differential equations*, *difference equations*, *relations between variables*). The *MM* can be based on either *knowledge of fundamental physics*, *empirical observations*, or a *hybrid of both*.
Therefore, monitoring methods based on *quantitative* models are appropriated, particularly in dynamic context when the available process information makes it possible to use the physics principles of the process. *(Lorenz, 1996)* interpreted analytical modeling as a function of several levels: *system*, *physical* and *mathematical*.
We can distinguish two manners to perform the quantitative model as shown on *Figure III.4*. (*a*) *Analytically*, by using *MMs* of *physics* lows (*e.g., differential equations*, *difference equations*, *relations between variables*, *etc.*) and in this case the model is named *MMBTs* or *Analytical Model-based Technique (AMBT);* (*b*) By using *data*, and in this case,

the model is named *DDTs* *(Amann et al., 1999);* and by *combination* of both *methods*. In some references, *DDTs* are included in *AMBT*.

When a model is available, some *MBTs* applied in *FM* possess the advantages of being able to detect unknown faults and be applied quickly and online. In addition, *MBT*s have the potential of early detection of slowly developing faults in complex processes. On other side, in the field of the process supervision, the accuracy of the *MM*s for use in the *FDD* is required in order to be effective *(Chiang et al., 2001; Ng et al., 2001)*. However, the construction of such models is very difficult, due to the complex nature or non-linearity of the process, parameter variable in the time or lack of available measurements. Even the *model-based* is made, in many cases, may not provide accurate results *(Kiliç, 2005).*

III.4 - Analytical or Functional (Betta et al., 1996) Models

When observations coming from system are of numerical type and that one has a *MM* of the system, the *MMBT* is privileged for the monitoring.

The *analytical approach* uses first principles to construct *MM*s of the system *(Chiang et al., 2001; Ng et al., 2001).* A mathematical representation of the process must first be established in order to reproduce as accurately as possible the actual behavior of the system. This mathematical representation is usually developed on the fundamental laws of chemistry and physics such as the conservation of mass, heat, momentum balance, reaction kinetics *etc.*, the first and second principle of thermodynamics, equilibrium between phases, transfer laws. Furthermore, this model can be based on input-output data and can be dynamic, static, linear or *NL*. Different analytically-based approaches for monitoring have been developed by the community of the automatic *(Gertler, 1998)*. The common point between all these approaches is the need to have a good knowledge of the system *(Chiang et al., 2001; Ng et al., 2001; Sankavaram et al., 2009)* and of the input / output behavior of the process.

The study on model-based *FM* initiated in the early 1970s. Intensely motivated by the newly conventional observer theory at that time, the first model-based *FDe* method (*FDe* filter) was proposed by *(Beard, 1971).* Since then, the model-based *FM* theory and technique went from side to side a dynamic and rapid development and it is currently becoming an important field of automatic control theory and engineering. In the 70´s and 80´s, it was the control community that made the decisive contribution to the model-based *FDi* theory, while in 2000´s, the trends in the *FDi* theory are marked by enhanced contributions from this three areas: One, is the computer science community with knowledge and qualitative-based methods as well as the computational intelligent techniques.

MBTs have been extensively studied for *FDD* in dynamic systems and *AR* *(Chow, Willsky, 1984)* is the core concept that most *MBTs* are based on. In this case, the normal behavior of a system is represented by a *MM*. Sensory measurements are estimated analytically from other correlated measurements using the model (*Figure III.10*). Faults result in violations of the normal relationships represented in the model, leading to statistically abnormal changes in the model *residuals*, *i.e.*, differences between the analytical estimations and the actual measurements. Therefore, faults can be detected by testing these residuals statistically *(Isermann, 2006).* The form of the residual is given by:

$$R(t) = f(u(t), y(t), r(t), x(t), \theta(t)) \tag{III.1}$$

where $u(t)$ and $y(t)$ denotes measurable inputs and outputs respectively; $x(t)$ and $r(t)$ represent the state variables and disturbances, and θ are the process parameters. Process faults cause changes in state variables and model parameters. Based on a process model one can estimate $x(t)$ or $\theta(t)$ by observed $y(t)$ and $u(t)$. Residual evaluation is accomplished by threshold logic and decision function. Beside fixed thresholds, advanced robust adaptive residual evaluators exist *(Frank, Ding, 1997).*

Different approaches for *quantitative* models for *FDe* were developed since the seventies *(Isermann, 1984).* The most used techniques for the generation of residuals for *FDe*, based on analytical models, were presented and analyzed by *(Chiang et al., 2001; Ng et al., 2001; Isermann, 2005)*.

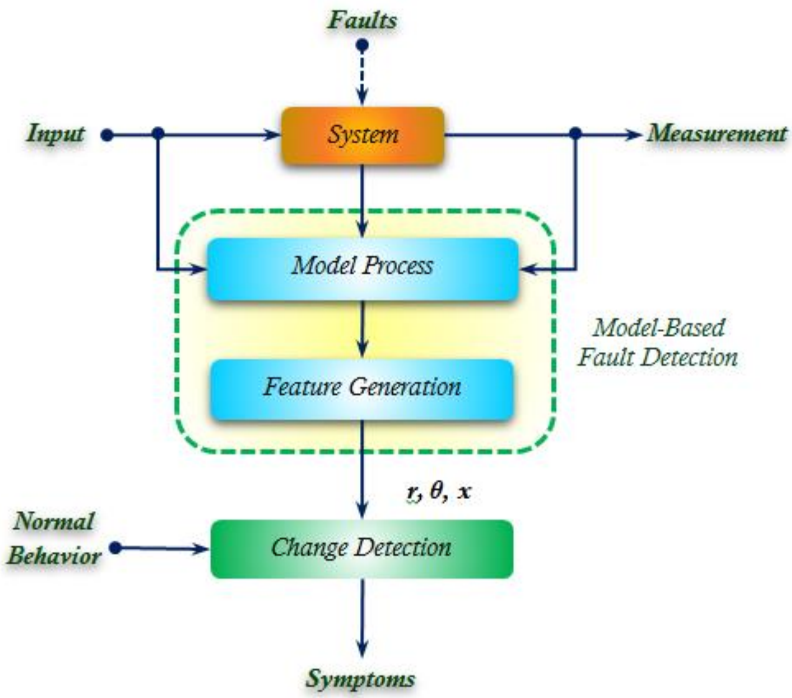


Figure III.10 - Process model-based fault detection (Miljković, 2011).

Most of the *ABTs* for *FDe* are decomposed mainly into *three* major groups as shown by *Figure III.11* *(Venkatasubramanian et al., 2003a; Samy et al., 2011)* which are (*a*) *parameter estimation (Li, Jiang, 2004);* (*b*) *state estimation* from *KFs (Basseville, 1988), observers (Palma et al., 2002);* (*c*) and *parity relations* called also *parity equations, parity space* or *consistency relation (Gertler, 1998).*

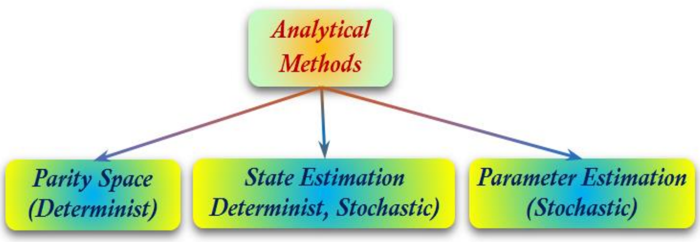


Figure III.11 - Analytical modeling methods.

Parameter estimators are identifiers of constant quantities of the system or which evolve slowly during time; called parameters *(Söderström, Stoica, 1989).* Variables are quantities which evolve in a significant way during time. The algorithms used to estimate these variables in the determinist case are the observers *(Gauthier, Kupka, 2001)* and in the stochastic case are the filters *(Jazwinski, 1970).* More details on *AMBTs* are available in *(Dubuisson, 2001; Zhang, Jiang, 2008).*

The *AMBTs* are computationally efficient. Moreover, it is easy to understand and interpret the *FDi* results when we apply these approaches. As expected, the main disadvantage of *AMBTs* is the overhead cost of constructing such analytical models. For complex systems, it is expensive and sometimes infeasible to generate an accurate model for the entire system.

III.4.1 - Parameter Estimation

An important *stochastic FDI* method is *parameter estimation* on the basis of system identification techniques (*e.g.,* least-square error and its derived methods), which was initialized by *(Bakiotis, 1979)* and then illustrated by *(Geiger, 1982)*. The first applications of *parameter estimation* approach were made by *(Isermann, 1994)*.
(Isermann, 1984) in his survey paper illustrated that process *FDi* can be achieved using the estimation of unmeasurable process parameters and/or state variables. This paper gave a generalized structure of *FDI* based on process models and unmeasurable quantities. This structure has been referred to in many subsequent papers *(Frank, 1990). (Isermann, 1987)* reported some experiences in the use of parameter estimation for process *FDI*. *(Isermann, Freyermuth, 1990)* studied on-line *FDI* systems using a combination of parameter estimation and heuristic process knowledge. This paper was followed by another survey paper *(Isermann, Freyermuth, 1991a),* and an application paper *(Isermann, Freyermuth, 1991b). (Isermann, 1991)* gave an application-oriented review of *parameter estimation FDI* methods based on a number of real or laboratory applications. Other development and applications of *parameter estimation FDI* approaches can be found in *(Isermann, Ballé, 1997).*

Process *parameters* or characteristic quantities are understood as *constants* or time-dependent coefficients which *appear* in the *mathematical* description of the *relationship* between the input and output signals in the process model.
In this approach, the faults are assumed to be reflected in system parameters (such as *friction*, *mass*, *viscosity*, *temperature*, *pressure*, *flows*, *capacitance*, *inductance*.), and only the model structure is needed to be known.
Parameter estimation estimates the model parameters or an aggregation of several physical parameters and uses a parametric model describing the system behavior by supposing that the parameters to be estimated are known at nominal operation. Therefore, they consist to identify the parameters characterizing the real operation, from input and output system measurements.
In some cases, a fault could occur due to changes in the system parameters. This can be expressed as a change in the i^{th} row and j^{th} column element of the matrix of the state space equations of the system. If the basic structure of the system is known, system parameters can be determined with parameter estimation methods by measuring input and output signals.

Faults of a dynamical system are reflected in *physical parameters* (*friction*, *mass*, *resistance*, capacitance, *inductance etc*.). In most practical cases the *process parameters* are partially *not known* or *not known at all*. They can be determined with *parameter-estimation methods* by measuring the input and output signal if the *basic model structure* is *known*. The basic idea of the *FDe* using *parameter method* is to identify the parameters of the actual process on-line which are compared with the reference parameters obtained initially under healthy conditions. The parameter estimation based *FDi* methods are very straight forward if the model parameters have an explicit mapping with the physical coefficients.
This method was well reviewed in the early survey papers *(Isermann, 2005)* and book *(Simani et al., 2002).*

The *idea* of using the *parameter identification approach*, *Figure III.12*, to detect the faults is done via estimation of the parameters of the *MM* due to following procedure, *(Frank, 1990)* : (*a*) *Choice* of *parametric model* of a system; (*b*) *Determination* of *relationship* between the *model parameters* θ_i and *physical parameters* p_i

$$\theta_i = f(p_i) \tag{III.2}$$

(*c*) *Identification* of model *parameter vector* θ using the input u and output y of the actual system (*d*) *Determination* of *physical parameter vector* p

$$p = f^{-1}(\theta) \tag{III.3}$$

(*e*) *Calculation* of *vector deviations*, Δp, from its nominal value taken from the nominal model; (*f*) *Decision* on a *fault* by exploiting the *relationships* between *faults* and *changes* in the *physical parameters*, Δp_i.

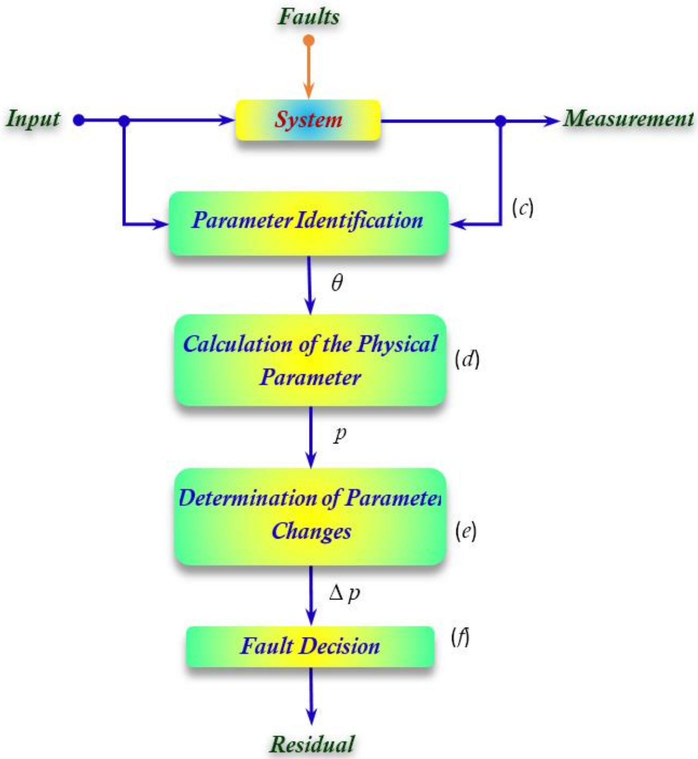


Figure III.12 - FDe with parameter estimation (Frank, 1996).

The basic idea behind the application of parameter estimation to *FDI* is that the parameters of the actual process are estimated on-line using well known parameter estimation methods. The results are compared with the parameters of the reference model obtained initially under fault-free conditions. The resulting deviations are the residuals on which any substantial discrepancy indicates a change in the process and may be interpreted as a fault. Therefore, deviations in the model parameters serve as the basis for detecting and isolating faults. Pioneering work in the development and application of this approach was done by *(Isermann, 1993).* Other important contributions were made *(Filbert, 1985)*. In real time application, it mostly uses *Recursive Least Squares* (*RLS*) as *parameter estimation* method.

III.4.2 - Observers, State Estimation

The process faults can be indicated by internal, non-measurable process state variables, which can be estimated or reconstructed from the measurable signals by using a known process model.
The concept of observer-based approaches is to estimate the system variables (state or outputs) such as *Luenberger observer* for the *deterministic case* or a *KF* for the *stochastic case*, and use the estimate errors as residuals. Observers can be applied for *FDe* in *deterministic environment* *(Li et al., 2006)* like *NR* *(Li, 2003)* when the process parameters are known *(Isermann, 2005)*.

The *state* estimation can be carried out using different methods depending on how stochastic the model is *(Isermann, 1984).* In the *determinist case* by means of *observers*: for example, in the frequency domain, the generalized observers or in the temporal domain, the *Lemberger observers* *(Lemberger, 1971)* or in the *stochastic case*

by means of *filters*: for example, *KF* *(Willsky, 1976)* or *FDe* filters *(Massoumnia, 1986).* These two types of methods, present analogies in their formulation and their operation, can be represented with the *Figure III.13*.
The structure of the detection using *KF* technique is similar to observers. The major difference is, *KF* recursively estimates model matrices assuming that the measurement noise is white and Gaussian.

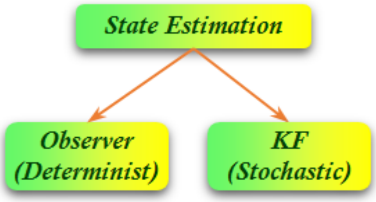


Figure III.13 - Type of stat estimation.

III.4.2.1 - Observers

The *first use* of *observers* for *FDD* is dated back to the early *1970s*. *(Beard, 1971)* at *Massachusetts Institute of Technology* (*MIT)* was the first to apply observer-based *FDe* models. Since then different observers have been applied to sensor *FDe* of steam generators *(Seliger, Koppen-Seliger, 1995),* power plants *(Simani, 1999),* turbofan engines *(Dassanake et al., 2000), HE*s *(Astorga-Zaragoza et al., 2008)* and coal mills *(Odgaard, Mataji, 2008).*

Observers can be applied for *FDe* in *deterministic environment* *(Li et al., 2006)* like *NR* when the process parameters are known *(Isermann, 2005).* In recent years, many solutions for the *FDI* problem that use an observer-based approach have been proposed. The *advantage* of using an *observer* is the flexibility to select its gains that leads to a rich variety of *FDI* schemes *(Frank, Ding, 1997).*
The essence of the *advanced observers* is to construct an augmented system by introducing the concerned fault as an additional state and the extended state vector is thereafter estimated, leading to the estimates of the concerned fault signal together with original system states. Therefore, the *advanced observers* are also called *simultaneous state and fault observers*.
Advanced observer techniques such as *Proportional And Integral* (*PI*) *observers* *(Gao, 2008; Zhang et al., 2013), Proportional Multiple Integral* (*PMI*) *observers* *(Gao, Ho, 2004; (Koenig, 2005; Gao et al., 2007), adaptive observer (Gholizadeh, Salmasi, 2014; Liu et al., 2015), sliding mode observers (Alwi, Edwards, 2014; Han et al., 2014),* and *descriptor observers* *(Gao, Wang, 2006; Gao et al., 2008)* are usually utilized for *Fest / reconstruction*. Others methods for the design of *FM* observers *(Frank et al., 2000b)* include an *Eigen structure assignment approach*, an *UIO approach*, and a *geometric approach proposed* in *(Patton, Chen, 1997).*
The above advanced observer techniques are in an advantage position either for reconstructing slow-varying additive faults (PI, and PMI observers), slow-varying parameter faults (adaptive observers), actuator faults with sinusoidal waveforms (sliding mode observers), and high-frequency sensor faults (descriptor system approaches).
(Clark et al., 1975) first applied *Luenberger observers* for *FDe* and various sensor *FIso* schemes were later developed *(Clark, 1979).* The survey paper *(Frank, 1987)* established the position of observer-based methods in model-based *FDI*. In this survey paper, many different schemes using both linear and *NL* observers are reviewed and some application examples were presented. *(Yan, Edwards, 2008)* used *sliding mode observers* to estimate the system state variables then a fault-reconstruction scheme is proposed to approximate the fault signal and it can be implemented online.
Actually, the above observer techniques may be integrated or *combined* in order to solve engineering-oriented problems. For instance, in *(Zhang et al., 2013), integral observer*, *sliding observers* and *adaptive observers* are *combined* to reconstruct sensor faults for satellite control systems. In *(Gao et al., 2008), PI observer* and *descriptor observer techniques* are *integrated* to estimate parameter faults for an aero engine system.

III.4.2.2 - State Estimation

In parallel with the development of the *FDi* for *deterministic systems*, *stochastic approaches* were also developed for *FDi* in the early 1970s. A general *FDD* procedure was first proposed in *(Mehra, Peschon, 1971)* by using residuals (or innovations) generated by *KFs* with similar structure to observers, where the faults were diagnosed by statistic testing on whiteness, mean and covariance of the residuals. The state-estimation based methods are typically useful when all of the state parameters are not observable.

The purpose of *state estimation methods* is to reconstruct the unmeasurable states and outputs of the system from the available measurement of inputs and outputs *(Li et al., 2006; Fonda et al., 2010).* Therefore, the state-estimation based methods are typically useful when all of the state parameters are not observable. By opposition of open loop methods (*space of parity*), this strategy works in closed loop as shown by *Figure III.14*. For more details on *state estimation techniques* for *FDI see (Witczak, 2007).*

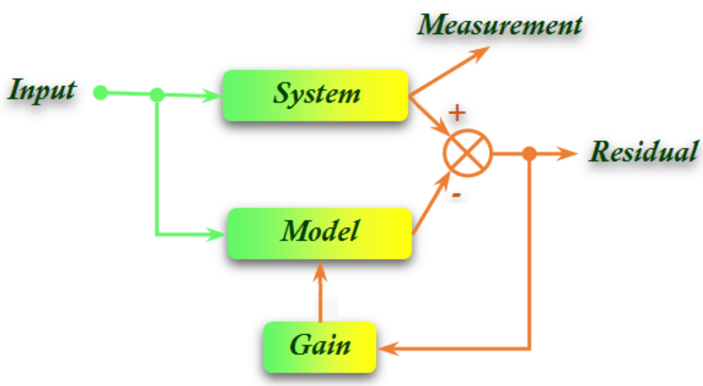


Figure III.14 - Residual generation based on stat estimation model.

The *KF (Xue, Guo, 2010)* is one of the main *state-estimation* and quite popular *(Kobayashi, Simon, 2003; Naderi et al., 2011)* algorithms which is widely applied to *linear dynamical systems (Hereford, Galyen, 2004; Hereford, 2006)* because of their systematic design, noise disposal and enhance sensitivity. The usual way to deal with measurement uncertainty is to apply techniques based on the *KF*, which should be able to estimate engine performance parameters and measurement biases in the presence of noise. Therefore, they are used in a *noisy environment (Hereford, 2006; Elnokity et al., 2012)*. When used in practice, *KF*-based estimation techniques are affected by several drawbacks *(Zedda, Singh, 1999),* resulting in inaccuracy and lack of reliability.

Faults can be modeled as state variable changes. Limiting consideration to *LS*s, the actual system may be given in continuous time by state equations.

KF has a systematic design, noise disposal and enhances sensitivity to produce the effective results. Therefore, most of the early research work on the *FDe* problem was based on the application of *KF* techniques *(Bundick, 1991).*

KF-based observer design has been used by *(Zhang et al., 2004; Ryerson, 2006).* It was used for *FDI* in a dynamic system *(Huang et al., 2012)* and also in other application examples of *KF*-based *FM* can be found in *(Lall et al., 2012*; *Foo, et al., 2013)* respectively for electronic systems under mechanical shock, and permanent-magnet synchronous motors.

Further researches have led to a couple of modified *KF* techniques for *FDi*, such as *extended KFs* (*EKFs*), *unscented KF*s, *adaptive KF*s, and *augmented state KF*s. Unlike the conventional *KF*s, the *EKF* can be used to monitor the faults in a *NL* industrial process. The *Unscented Kalman Filter (UKF)* depending on a more accurate stochastic approximation, *i.e., unscented transform*, can better capture the true mean and covariance leading to better *FDi* performance *(Liu et al., 2014*; *Laila et al., 2013). Adaptive KF*s can be employed to tune process noise covariance matrix, or measurement noise covariance matrix in order to obtain satisfactory *FM* *(Izadian, 2013)*. The *augmented state KF*s can be utilized to simultaneously estimate system states and fault signals *(Hmida et al., 2012)*.

III.4.3 - Parity Relations

The *parity relation approaches* were originally proposed in the early 1980s by *(Chow, Willsky, 1984)* although he used a different terminology. Unfortunately, his papers have not received enough attention due to their limited availability. This approach was later, independently proposed by *(Chow, Willsky, 1984)*, and a number of different forms of *parity space* approach have been introduced. For example, *(Gertler, 1988)* gave a parity relation design method in the domain. *(Chen, Zhang, 1991)* developed a stochastic system *FDI* approach based upon a direct development of the parity vector concept used in *HR*. This technique is improved by *(Massoumnia, Van Der Velde, 1998)*, then have introduced for the *FDI* by *(Gerfler, 1997)*.

Parity relations are subjected to a linear dynamic transformation and are rearranged direct input-output model equation in a particular space, named *parity space* *(Gertler, 1998)*. The *parity relation method* checks the consistency (parity) of the measurements with regard to their estimated given by the model of mathematical equations of the system to generate residuals (parity vector). This allows eliminating the unknowns by means of redundancy.
Two sorts of parity space according to the equation nature with which the model is built. They are *state-space-based* and *input-output-based* *(Zhang, Jiang, 2008)*. The residual in the parity space approach is either defined based on the *input-output* operator representation of the system *(Frank et al., 2000b)* as:

$$R(s) = [Y(s) - G(s)\ U(s)]\ V(s) \tag{3.4}$$

where $Y(s)$, $U(s)$, $G(s)$ and $V(s)$ represents respectively the output, the input, the nominal process model and a filter yet free to select.

The basis configuration of the parity space approach in input-output format, first described by *(Gertler, 1991)*, is shown in *Figure III.15*. The residual can be calculated with the aid of *Laplace transform* *(Frank, 1996)*.

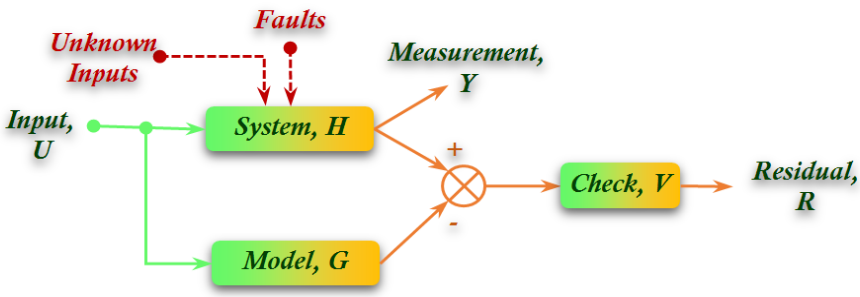


Figure III.15 - Redundancy based on parity relations (Touaf, 2005).

The *parity relation* approach can be applied to either *time-domain state-space model* or *frequency-domain input-output model*, which is well revisited by the books *(Chen, Patton, 1999; Ding, 2008)*. Recently, the parity relation method is *extended* for *FM* for more complex models such as *TS fuzzy NL systems* *(Nguang et al., 2007)* and *fuzzy tree models* *(Zhang et al., 2013)* and applied to various industrial systems such as aircraft control surface actuators *(Odendaal, Jones, 2014)* and electromechanical brake systems *(Huang, Huh, 2014)*.
Parity approach is known by its simplicity. However, accurate and complete *MM*s are not always easy to obtain, even impossible, for complex processes such as chemical and nuclear processes.

III.4.4 - Methods for Non-Linear Systems

While proving to be successful *MMBTs* are usually *limited* to *LTISs*. But in most cases, the assumption that the system is entirety linear is not often valid *(Campa et al., 2002a; An, 1998).* Therefore, these techniques (*i.e., parameter estimation*, *observers*, *state estimation* and *parity equations*) might perform inadequately, in the *NL* regions.

Novel *MMBTs* for *FDI* of *NL systems* include *adaptive estimation schemes (Zhang et al., 2002; Jiang, Chowdhury, 2005)* where the model is continuously tuned to fit the time varying system. Other *MMBTs* can be found in *(Chen, Patton, 1999; Korbicz et al., 2004)* and the references therein and some of them usually suffer from the lack of an appropriate mathematical description of the system being considered.

If there is no, or not sufficiently accurate analytical models, then the one feasible way is to use the so-called *AI* techniques, such as *NNs (Korbicz et al., 2004; Ruano, 2005)* which is steadily growing in the *FDe field (Isermann, Ballé, 1997).* Furthermore, recent literature has seen efforts been made to address these issues, particularly with the linearity assumption of the *KF*s *(Julier et al., 1997).* Several versions of the *KF* have been developed and applied to various fault tolerance and state estimation problems in *NL* systems *(Samy et al., 2010; Mrugalski, 2013).*

In conclusion, the application of any *model-based FDI* scheme is primarily a question of the *quality* of the *available MM* of the system *(Frank, 1990).* The success of the *MMBT* is *heavily dependent* on the *quality* of the *models,* so *accurate* modeling for a *complex NL system* is very difficult to *achieve* in practice *(Far, 2007).* Furthermore, the *main problems* associated with the application of these *FDe* schemes are their suitability only for *linear time invariant systems* and their applicability only when the system *model* is *identical* to the *filter* or observer model and/or with a *high signal-to-noise ratio (Napolitano et al., 2000).* The *sensitivity* to *modeling errors* has become the key *problem* in the application *of MMBTs (Frank, 1990).* Hence, actually a great effort is concentrated on the development and enhancement of *NL* and *robust* approaches.

III.4.5 - Advantages and Drawbacks

AMBTs for *linear* and *NL* time invariant systems are very appealing due to their advantages of speed in terms of on-board real-time implementation are the most *accurate* and *reliable*. The success of the *MMBT* is dependent on the quality of the models and the fidelity of the system. In the real world, most of such methods can suffer from serious drawbacks such as *computational complexity* and in terms of robustness to time *varying system parameters, modeling discrepancies* between real system and *MM*, *disturbances, noise*, and to *non-linearities* which can engender errors in the model. So, reliability of *FM* often decreases as this system factors increase. In some practical cases, when the level of these factors is important, it is almost impossible to obtain a model that exactly matches the process behavior *(Mohamed, Ibrahim, 2002).* In this case, the task of modeling is often tedious and *analytical models* cannot be computed or give unsatisfactory results *(Fuente et al., 2012; Kourd et al., 2013).*

Indeed, the main common *drawback* of the *MMBTs* of *FDD* is the requirement of a precise, accurate (exact) and complete *MM* of the system to be monitored *(Kempowsky, 2004; Kourd et al., 2013)*.

Unfortunately, the generation of such model (*complete* and *perfectly accurate*) of a large6scale physical systems is not always possible and not easy to achieve (*never available*) in practice or economical in an industrial environment, and requires an *effort* which is *proportional* to the *size (high dimensionality), complexity* and *nonlinearity* of the *process (Chiang et al., 2001; Ng et al., 2001; Fuente et al., 2012)* such as in chemical and nuclear processes. Hence, the practical applications of *MMBTs* methods are not adequate and very limited *(Ma, Jiang, 2011; Alzghoul et al., 2014).* Sometimes the task of modeling is often *tedious* and models cannot be computed give *unsatisfactory results (Kourd et al., 2013; Fuente et al., 2012).* Parameter or state changes are determined using estimation techniques *(Sorsa, Koivo, 1993).* In practice, the heavy load caused by the estimation can also be a

problem *(Sorsa, Koivo, 1993)*. Usually, *(Chen, Patton, 1999; Korbicz et al., 2004)* and the references therein, all usually *suffer* from the lack of an *appropriate mathematical description* of the system being considered.
Usually, the *parameters* of the *system* may *vary* with time in an uncertain manner, and the *characteristics* of the *disturbances* and *noise* are *unknown* so that the system *cannot* be *modeled accurately*. Hence, there is always a mismatch between the actual process and its *MM* even if there are no process faults. Apart from the modeling used for the purpose of control, such discrepancies cause fundamental methodology difficulties in *FDI* applications. They constitute a source of false and missed alarms which can corrupt the *FDI* system performance to such an extent that it may even become totally useless. The uncertainty of the model could reduce the reliability of *FDe* when it is not considered. Therefore, the *effect* of *modeling* uncertainties is therefore the most crucial point in the model-based *FDI* concept, and the solution of this problem is the key for its practical applicability *(Patton, Chen, 1997)*.
On other side, *models* are mostly difficult to change afterward. The build-up of a *model-based detection* system requires a lot of effort because a variation of one or more system parameter(s) lead to changing the form and coefficients of many characteristically equations of system. The *KF* approach uses the system model to *detect* and *isolate* sensor failures. Thus, it is strongly dependent upon a high fidelity of the model which may become an obstacle in the implementation of a complex system. For more details on *drawback* of *MMBTs see (Napolitano et al., 1995)*.
However, in the event of multiple sensor faults, model estimates can be inaccurate and so real-world applications tend to maintain a slight degree of *HR (Hussain et al., 2015)*. So, the change, in controller parameters or structure, allows avoiding the consequences of a fault *(Blanke et al., 2001)*.
On other side, *MMBTs* (involving the solution of ordinary differential equations) usually do not account for the combination of analog and discrete processes.

In conclusion, if these anomalies are not handled properly in a specific way when implementing *FDD* systems, there is no guaranty that the residuals be sensitive to faults. Furthermore, in some cases, the suppression of the effect of the model anomalies has a negative effect on the residual sensitivity. In both cases, *false* and *missed alarms* can be meet which finally has strong impact on *FDD* performance; therefore, the adaptability of these approaches in real world changes is not warranted. As a result, practical applications of *MBT*s in real systems are still very limited.
Finally, these *disadvantages* increase the *necessity* of *using alternative approaches*: *NN*, *case-based reasoning*, and *knowledge-based approach*.

III.5 - Data-Driven Models

The success of the *MBTs* depends on the fidelity of the system or the component model expressed in a mathematical form. In the context of *complex* and *NL* processes, we have already mentioned that the generation of an appropriate *accurate* and *reliable* analytical model, and flexible frameworks is often very *difficult* and *constitute* a real challenge.
When the model is incomplete or not available at all, one solution is to use *DDTs (Venkatasubramanian et al., 2003c* as a promising supplement to model-based *FDiso* to carry out *system analysis, FM* and *industrial control*. Indeed, *DDTs* attracts significant attention in the fact they do not need an explicit model of a system; they are used as *model-free* based on transformations of set of measurements. The main advantage of data-driven modeling approach is the reduced time and effort in developing system model. Therefore, *DDTs* are flexible for applications in practical systems and have been favorable choices for *FDD* in various industries *(Ma, 2015)*.

Methods based on data processing rely on so-called *behavioral models*, and when data is used in *model-free* is generally a large amount of process-historical data of the process is needed (*Tajik, 2015)* to present them as a priori knowledge for the monitoring. The idea is to analyze these data by different techniques in order to

propose a model of behavior. These data are thus transformed into a source of knowledge for the *FDi* system, during a so-called *feature extraction* step. At this level, there are usually two types of extraction techniques, whether *statistical* or *not* (Olivier-Maget, 2007). In the *statistical category* one find mainly *PCA*, *data classification* and *SR* while in *non- statistical category*, one has the frequency approach and *NNs*.
The *PCA* considered as a *DDT* has been successfully used to detect faults, by many researchers such as (Villegas et al., 2010; Fuente et al., 2012). Also like *PCA*, we find the *PLS* (Mandal, 2015).

In general, *DDTs* for *FM* are broadly classified into *FL, NNs*, *clustering*, *Self-Organizing Maps* (*SOM*), *statistical methods, ESs* and *PR*.
DDTs can be further *subdivided* to *univariate* or *multivariate statistical analysis.* That is, whether the *data stream* of one *measured attribute* is *dependent* on *another single attribute* (*univariate*) or it is *dependent* on *several other attributes* (*multivariate*). Some faults can only be detected within the context of another data instance; therefore, *multivariate approaches* are *preferable* to *univariate approaches* (Pettersson, 2005).
(Dash, Venkatasubramanian, 2000; Zhang, Jiang, 2008) divided *DDTs* into two categories, *quantitative* and *qualitative* as shown in *Figure III.4*. The *quantitative* methods include *statistical approaches* such as *PCA*, *PLS*, statistical classifiers and *NNs*. The *qualitative* methods include *ES*, *FL*, *PR*, frequency and *TFA*, and qualitative trend analysis (Zhang, Jiang, 2008).
DDTs can be divided into *two groups*: *statistical* and *non-statistical methods* (Alzghoul et al., 2014). *NNs* (Mcculloch, Pitts, 1943), *SOM* (Kohonen, 1982), *nearest neighbors* (Dasarathy, 1991) are examples of *non-statistical DDTs*.
Data-based monitoring methods can be further classified into *input MBTs* and *input-output MBTs*. *Input MBTs* only require the data matrix of the input process variables, while *input-output MBTs* require both the input and output data matrices in order to formulate a model and carry out *FDe* (Mansouri et al., 2016). Input *MBT*s are sometimes utilized when the input-output models cannot be formed due to the high dimensionality and complexity of a system being monitored (Jolliffe, 2002). However, input-output *MBT*s do have the added advantage of being able to detect faults in both the process and the variables (Mansouri et al., 2016).

III.5.1 - Quantitative Model

Several *models* used in redundancy to generate residual are based on *data* and *AI methods* (Sorsa et al., 1991; Racoceanu, 2003). *NNs* represent the main *quantitative* approaches applied in this context (Samanta, 2004). *So, DDTs* are popular choices for *FDI* in systems.

In *FM* literature, one can find a huge overlap between *analytical model-based* and *DDTs*. As previously mentioned, *analytical model-based FM* methods usually deploy a model developed based on some fundamental understanding of the physics of the plant or process contrary to *DDTs*. *DDTs* for *FM* have the advantage to not require the knowledge of mathematical or structural model of the plant or process, but a *model derived* from known and measured input and output process data.

The fundamental idea of *quantitative DDTs* is to generate an *empirical model* of the process which relies on mathematically relationships between correlated measurements, such as inputs and outputs, within a system. However, the *relationships* can be formulated in an implicit way by training an *empirical model* through analysis of *fault-free training data* obtained during *normal operations*. This *model* is then used to estimate true values of new measurements. These values against the real process data measurement are used to generate residual for *FDe* and *FDi*.
Popular algorithms in this context include *PCA*, *NN* (Venkatasubramanian et al., 2003a), *Multivariate State Estimation Technique* (*MSET*) (Hines, Usynin, 2005, *AAKR* (Garvey, Hines, 2006), and cross calibration (Hashemian, 2006). *NN* and *MSET* have been used for a large variety of *FDD* applications (Nieman, Singer, 2002; Hines, Davis, 2005).

The *learning data* can either be collected from the process itself or from a simulation model *(Crowther et al., 1998).* The second possibility is of special interest for collecting data of the different faulty situations in order to test the residual generator, since usually those kinds of data are not available at the real process *(Zhang, 2000).*

III.5.2 - Machine Learning

Machine learning (ML) is another *DDT* to produce an online *FDD model* by using learning algorithm, have been widely used in the process industry. Learning off-line reduces the online computational load, but produces a static model, which may not fit new behaviors.

ML uses the theory of *statistics* is the process to build an inductive model that learns from a limited amount of data without specialist intervention to accurately *predict events* in the future particularly, the class of unlabeled data. Learning in models translates into fitting a model's parameters to a specific dataset, iteratively updating them with several passes through the data until a specific predefined function is minimized *(Stetco, 2019).* This learning implies best characterize underlying set of structures (or patterns) that are useful to understand relationships in data that might not be exactly similar to that on which learning occurred.
Furthermore, *ML* is a scientific discipline that explores the construction and study of algorithms that can learn from data. Such algorithms operate by building a model based on inputs and using that to make predictions or decisions, rather than following only explicitly programmed instructions. The model learning can take place offline, *e.g.,* on past observations that were recorded from previous operations, as well as online.
Informative features are selected or extracted from a dataset. According to these features, an *FDD* model is learned from a dataset. The learned model provides the ability to classify new unseen data. In particular, the *FDD* model is used to *classify* online data that is produced in real time by the *system*, determining whether or not the data expresses a fault and even associates its *FDi*.

Several different models have been suggested for learning from data. *SVM* and *NNs* are two common models that have been used in *ML* for *FDi* and *prognostic*. *ML* methods can be partitioned into four different categories: *unsupervised learning*, *supervised learning*, *semi-supervised learning*, and *reinforcement learning* (*Figure III.16*). Two of the most widely adopted *ML* methods are *supervised learning* and *unsupervised learning*, which may account 80-90 percent of all industry applications. While *semi-supervised learning* methods have recently been used for *data classification* and *regression* in the process industry, the *reinforcement learning* has rarely been used in this area.

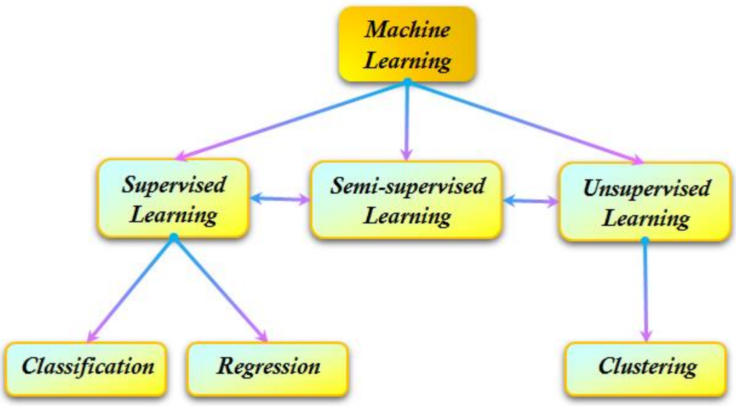


Figure III.16 - ML methods applied in the process industry (Ge, 2017).

Supervised learning predicts an output variable using labeled input data, while *unsupervised learning* draws inferences from data without labeled inputs, *i.e. Supervised approaches* require a *classified* dataset for model creation, while *unsupervised approaches* do not. In the latest, this means that the data only consists of a set of inputs without any corresponding targets. For *supervised learning* we distinguish between models that predict a numeric variables (*regression*) or a categorical variables (*classifiers*), *e.g.*, *process fault classification* try to classify the faults into different categories an if the desired output consists of one or more continuous variables, then the task of supervised learning is called *regression* *(Stetco, 2019).*

Semi-supervised learning has recently attracted much attention in the process industry, which is applied for similar purposes as *supervised learning*. In *semi-supervised learning*, a small amount of labeled data and a large amount of unlabeled data are typical assumed for modeling. *Semi-supervised learning* is particularly useful when the cost associated with labeling is too high to allow for a fully labeled training process. Instead, unlabeled data is much cheaper and takes less effort to acquire from the process. This type of *ML methods* can also be used for data *classification*, *regression* and *prediction* of key performance indices of the process. With appropriate information integrations, model structure modifications and training improvements, both *unsupervised learning* and *supervised learning methods* can be made *semi-supervised*. Therefore, *semi-supervised* learning can be considered as a bridge connecting unsupervised learning and supervised learning.

III.5.2.1 - Classification

The classification of patterns of measured quantities for *FM* purposes is an important area of research with practical applications in a variety of fields ranging from industrial to medical. In particular, the classification of faults in nuclear components represents a fundamental task for the operation, control and accident management of *NPP*s.

Classification *(Matic et al., 2010a)* is *supervised learning* technique used to separate samples into different categories by finding common features between samples of known classes then to assign a new observation to a predefined class or category (*Figure III.17*). Therefore, classification model is created from training data, and then it is used to classify new instances. So, representative *training data* play a very important role in classification which are used to extract information. For monitoring, a classifier is an algorithm that takes data or transformed data (*e.g.,* features) as an input and emits out a decision about the health status of the system. The *classification* method is typically an *off-line* method where the *measurement* data are first *collected,* then the *characteristic features* are *extracted* and *selected* and finally, the data is *classified* *(Maio et al., 2011).*

Figure III.17 - Block diagram of the classification.

Many studies have already made it possible to show classification methods for *FDi*, particularly in the context of complex systems *(Ribes et al., 2002).* The methods range from the more classical methods, such as *statistical classifiers* (the *Bayesian classifier*, the *K nearest neighbors*) *(Casimir, 2003; Marie-Joseph, 2003),* to the *NNs* *(Lurette et al., 2001).* A great variety of pattern classification methods have been developed such as *K-Nearest K-NN; NNs*; *naive Bayes classifier*, *HMM*; *SVM, Logistic Regression (LR)*; *FL*; *Decision Trees (DTs); random forest;* and the *hybrid* and *ensemble of different models*. Details regarding those models and the training processes can be found in the rich literature on *PR* and *ML* *(Bishop, 2006; Webb, Copsey, 2011).* More details for *classification method* are available in *(Bentoumi, 2004).*

For *FDD* application, the class labels are related to specific fault hypotheses. The *classifier* is trained offline using training data with known fault classes. When new measurement data become available, their class labels are estimated by the classifier; thus, the current condition of the system is determined from the class label assignment *(Widodo, Yang, 2007).*

Overall, detection consists in deciding between two hypotheses presence of faults or non-presence of faults (problem with two classes). When classification is used for detection problem, a number of classes (hypotheses) is used rather than two *(Bentoumi, 2004).*

Relevant symptoms are identified to be representative of each type of failure. The relationships between symptoms and faults are obtained by supervised learning when faults are known a priori, and the system decision is tuned to correspond to the right answer from a training set of known examples.

The approaches for detection and classification of faults can be approached *simultaneously*, which consists in breaking down the global problem into particular sub-problems of detection and classification to be solved. The second way performs detection and classification *successively* by treating the two issues separately *(Bentoumi, 2004).*

When, *FDi* is essentially seen as a *classification problem*, the main purpose is to construct a correspondence block such as from a set of information describing the current situation of the process; it is possible to obtain the probable *causes* of the *abnormal* situations. However, when the *FDi* is based on multiple observations, these observations are grouped together to form classes that define a situation or operation mode of the process, to which a new observation will be compared to be identified. In other words, the purpose of the *FDi* is to identify the mode of operation of a system based on observations on it. Therefore, the *FDi* system is a *classifier* that recognize, in real time, the actual situation represented by a new symptom vector and associate it to one of the known faults. The classifier may also have some on-line learning capacity to deal with unknown faults.

Several *CM* tasks have been explored using classification. *(Verma, Kusiak, 2012)* developed *generator brush failure classification* models based on *Supervisory, Control, and Data Acquisition* (*SCADA*) data sampled every 10 min. For the relevant signal selection step, they used *chi-square* (filter technique), *boosting tree* (embedded method) and a *wrapper method* with genetic search and found 10 signals to be predictive of generator brush failure (nacelle revolution, drive train acceleration, *etc.*). Their results show that brush failures can be predicted with reasonable accuracy 12 *h* before they occur. *(Leahy et al., 2018)* considered *three generator fault classification* scenarios: *FDe* (two cases: fault and other), *FDi* (five classes including generator heating, power feeder cable, generator excitation, air cooling malfunction faults and other) and *fault prognosis* with the aim to predict faults at time intervals before they occurred. The data used came from a 3*MW* wind turbine situated in Ireland; *(Leahy et al., 2018)* selected 29 features from the *SCADA* system to be used in *classification*. Given the unbalanced class data, different under sampling and oversampling procedures were used when training *SVM* classifiers. *(Tang et al., 2014)* built a *classifier* to identify gear, bearings, shaft and general transmission failures. They performed *NL* dimensionality reduction of vibration signals using Orthogonal Neighborhood Preserving Embedding (*ONPE*) *(Liu et al., 2006)* with Shannon *Wavelet SVM* (*SWSVM*). *(Santos et al., 2015)* proposed an *SVM classification-based method* to detect several types of faults related to rotor blade imbalance and misalignment (or a combination of both) on simulated data. They compare different *SVM* kernels to *NN*s and find that the best accuracy is obtained using a linear *kernel SVM* (suggesting that the data is linearly separable). As opposed to other kernels (such as *Gaussian*), a linear kernel has only one parameter, which reduces training and tuning time.

III.5.2.2 - Clustering

Clustering, also called *unsupervised classification*, is *unsupervised* technique used to group similar instances on the basis of *features* such that the objects in the same cluster are more similar to each other than to those in another cluster. Clustering does not assign predefined label to each and every group so, it traits a not labeled data structure and does *not require training* data *(Gan et al., 2007; Webb, Copsey, 2011).*

In general, based on the cluster structure which they produce*, clustering methods* may be *divided* into *two categories*: *hierarchical* and *non-hierarchical*. *Hierarchical method* seeks to build a hierarchy of clusters. Strategies for hierarchical clustering generally fall into two types: *Agglomerative*: This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. *Divisive*: This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy. *Non-hierarchical* method product directly one partition in a fixed number of classes.

Clustering is widely used in *PR*, *FDi*, data mining, image analysis and *ML*, and scientific and engineering analysis. One of the best known and most popular clustering algorithms is the k-means algorithm. The algorithm is efficient at clustering large data sets because its computational complexity only grows linearly with the number of data points. However, the algorithm may converge to solutions that are not optimal. Some of the most commonly used clustering algorithms include *Fuzzy c-means clustering (Liu et al., 2009).* Spectral clustering is a relatively new algorithm *(Ng et al., 2001; Von Luxburg, 2007) Normalized Cuts (NCuts) (Shi, Malik, 2000)* and *Density-Based Spatial Clustering of Applications with Noise* (*DBSCAN*) *(Ester et al., 1996).* In recent developments, some algorithms have been presented from different focuses, including the *affinity propagation algorithm (Frey, Dueck, 2007), spectral clustering (Zhu et al., 2014b), dominant sets (Pavan, Pelillo, 2007), density peak based algorithm (Rodriguez, Laio, 2014)* and *others (Panagiotakis et al., 2013; Wang et al., 2015).* The *Dominant Sets (DSets)* algorithm defines dominant set as a non-parametric concept of a *cluster*, and generates the clusters sequentially. Based on the nice properties, the *DSets* algorithm has been applied successfully in image segmentation *(Pavan, Pelillo, 2007, Hou et al., 2016a),* object detection *(Yang et al., 2012)* and object classification *(Hou, Pelillo, 2013*; *Hou et al., 2016b), etc.*

III.5.2.3 - Regression

Regression is a set of statistical methods used to analyze the relation of a variable with regard to one or several others. Therefore, regression is the operation which consists to adjust a straight line (or another mathematical curve) closer possible to a certain number of observed points. On *Figure III.18*, points are a graphic representation of the historic data-base which we want to use them to predict their evolution. Data are regrouped in a narrow ribbon, so it is possible to pass "in best" a curve through this cloud of points, and to consider that this curve is an approximate but satisfactory model of the reality.

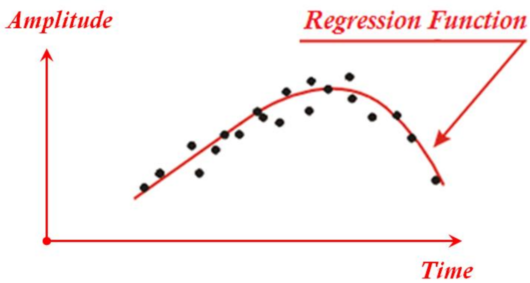


Figure III.18 - Illustrative Example of the Regression Function.

The most known model of regression is the model of *linear regression*. The model of *quantity regression* is used if we are interested by the conditional quantity of the distribution of unpredictable variable knowing the vector of random variable *x*. *LR* is commonly used when the explained variable is binomial random.
Non-parametric regression is used when the functional shape of the regression is unknown.

The *regression analysis* is also used to determine among independent variables which have relation with a dependent variable, and to investigate the forms of these relations. In some cases, *regression analysis* can be used to deduct causal relations among dependent and independent variables.

For *FDe*, the task is to identify how signals and features are related to outputs in different components. This relationship is captured by fitting regression models when the system is in a healthy state. When new data comes in, it is compared to what the model predicts for a healthy state and if a deviation is found for several consecutive time intervals, an alarm is raised. Behavior of a component (from low to high granularities) can be captured through regressions of different complexities (from a simple linear model to a complex *NL* one).

(Lapira et al., 2012) compared a regression model based on *FFNNs* with two unsupervised methods (*SOMs* and *Gaussian mixture models* (*GMMs*) trained on an operational large-scale onshore wind turbine. They *modeled the power curve* and *analyzed the system health* by using a new approach (confidence health value) based on residuals being greater than a given threshold during a given time segment. They found the *GMM* model presents a more gradual health change being more suitable in performance identified at being the best prediction. *(Schlechtingen, Santos, 2011)* investigated three models (*regression*, *NNs* and *autoregressive NNs*) that learn to *approximate* the *normal bearing temperature* using *SCADA* input signals such as power output, nacelle temperature, generator speed, generator stator temperature, *etc*. For identifying the lag and the signals which are related to the output signal (bearing temperature), cross correlation was used. They found that the *NL NN* approaches outperform the regression models. *(Guo et al., 2012)* built a regression model for generator faults based on the *NL* state estimate technique (*NSET*), introduced by Singer in *(Gross et al., 1997).*

III.5.3 - Supervised Learning Methods

Main *applications* of the *supervised ML method* include *process monitoring*, *fault classification* and *FId, online operating mode localization*, *soft sensor modeling and online applications*, *quality prediction and online estimation*, *key performance index prediction and diagnosis*, *etc*. Several different models have been suggested for learning from data. Some well commonly used *supervised learning methods* in the *monitoring* and *prognostics* of various systems include *principal component regression (PCR)*, *PLS*, *Fisher Discriminant Analysis (FiDiAn), Multivariate Linear Regression (MLR), NNs*, *SVM, nearest neighbor*, *Gaussian process regression*, *DT*, *random forest*, and *so on*.

PCR is a regression analysis technique that is based on *PCA* method. In this method, instead of regressing the dependent variable on the explanatory variables directly, the principal components of the explanatory variables which are extracted by the *PCA* method are used as *regressors (Jolliffe, 1982). PCR* is applied for the prediction and control in process industry such as with *(Xie, Kalivas, 1997; Yang, Gao, 2006).*

PLS regression is a statistical modeling method, which is quite similar to the *PCR* method. However, instead of finding hyperplanes of minimum variance between the response and independent variables, *PLS* finds a linear regression model by simultaneously projecting the predicted variables and the observable variables to the latent variable space *(Wold et al., 2001).* Therefore, the predicted variables and the observable variables are connected through the latent variables. In the process industry, *PLS* has been used for quality-related process monitoring, fault classification, soft sensor development and online applications, product quality predictions, and so on. *(Kruger et al., 2001)* proposed an extended *PLS* approach for enhanced *CM* of industrial processes. *(Zhang, 2009)* proposed a modified *PLS* method and combined with the independent component regression model for monitoring complex processes. *(Yu, 2012)* developed an adaptive *kernel PLS regression* method for soft sensor estimation and reliable quality prediction of *NL* multiphase batch processes. *(Godoy et al., 2014)* made several new contributions to *NL* process monitoring through the use of the *kernel PLS model*. A comparison and evaluation of key performance indicator-based multivariate statistics process monitoring has been carried out between the *PLS* method and other related approaches *(Zhang et al., 2015)*. *(Zho et al., 2010)* proposed a total projection form of the *PLS* model for the purpose of process monitoring. *(Peng et al., 2015)* developed a quality-related prediction and monitoring for multi-mode processes based on multiple *PLS* method, and applied it to an industrial hot strip mill.

FiDiAn is a supervised linear dimensionality reduction technique designed for data classification. The basic idea of *FiDiAn* is to seek a transformation matrix which maximizes the between-class scatter and minimizes the within-class scatter simultaneously *(McLachlan, 2004)*. Due to the ability of the *FiDiAn* method in dimensionality reduction and data classification, it has been widely used in the process industry. The method can be used directly for classification of different operating modes in the process, or to differentiate various faults that happen in the process. *(Chiang et al., 2004b)* proposed a *CMd* with *FiDiAn* and *SVMs* for *FDi* in industrial processes. *(Yu, 2011)* applied the localized *FiDiAn* method for monitoring complex chemical processes; *(Zhu, Zhu, 2011)* developed a novel *FDi* system by using pattern classification on kernel *FiDiAn* subspace; *(He et al., 2005)* proposed a new *FDi* method using fault directions in *FiDiAn*. *(Zhang et al., 2007)* developed a *NL* real-time process monitoring and *FDi* scheme based on *PCA* and kernel *FiDiAn*. *(Sumana et al., 2010)* proposed an improved *FDi* method by using dynamic kernel scatter-difference-based discriminant analysis.

MLR is a generalization of linear regression by considering more than one dependent variable *(Gholami, Shahbazian, 2015)*. In the process industry, there are lots of *MLR applications*, such as *soft sensor modeling between key indices/variables and ordinary process variables*, *quality prediction in the final product in batch processes*, *etc*. In the past years, main applications of the *MLR* methods are focused on soft sensor developments and prediction of product quality.

Owing to its powerful ability in *NL* approximation and adaptive learning, *NN* has been the most well-established *non-statistical* based *data-driven FDi* tool. Recent developments of the *NN* can be found in a variety of real-time applications, *e.g.*, for combustion engines *(Shatnawi, Al-Khassaweneh, 2014)*, steam turbine generator *(Yan et al., 2009)*, nuclear process *(Elnokity et al., 2012)*, induction machines *(Toma et al., 2013; Leite et al., 2009)* and power network quality *(Valtierra-Rodriguez et al., 2014)*.

SVM is an effective supervised tool for *ML* and *PR* method, based on *statistical* learning theory, which was originally developed in 1995 *(Cortes, Vapnik, 1995)* with associated learning algorithms that analyze data and recognize patterns, conventionally used for linear/*NL classification* and *regression analysis*. *SVM* is a discriminant model based on the finding decision boundary hyperplanes that best separate classes of instances, *i.e.* by leaving the widest possible margin to the instances closest to the margin (see *Figure III.19)*.

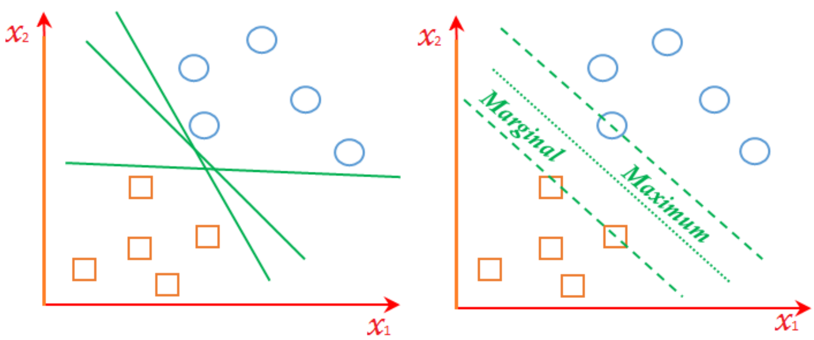


Figure III.19 - (Left) A multitude of linear decision boundaries separate the two classes. (Right) SVMs find support vectors which maximize the distance between decision hyperplanes and closest data points.

It implements by constructing an optimal separating hyper plane in the hidden feature space using quadratic programming to find a unique solution.

SVM is a powerful classifier that uses the concepts of *empirical risk minimization* (*ERM*) and structural risk minimization *(SRM)* *(Mamar, 2008)*. Given a set of training samples belonging to different *classes*, *SVM* find an *optimal decision boundary* (also called *hyperplane*) that minimize learning errors while maximizing the margin separating data from classes *(Burges, 1998)*. Therefore, *SVM* is also known as the *maximum margin classifier*. *Margin maximization* is a method of regularization that reduces the complexity of the classifier. It is used to penalize model parameters in the same way as the weight decay method which alters the large amplitude weights in an *MLP*. The penalization of *SVM* parameters in order to maximize the margin is a model selection method in implicit learning. This process produces a reduced set of prototypes that are part of the learning set and define the optimal separating hyperplane commonly referred to as *support vectors*.

These *support vectors* lie closest to the decision surface and can be used to *estimate the fault class* of a test feature vector. In the case of *NL classification*, where a linear boundary is not appropriate, a *kernel function* is used for mapping the data onto a higher dimensional feature space and the optimal hyper-plane that can separate different types of fault classes is then constructed yielding high classification accuracy. Some of the kernel functions that are commonly used are *polynomial*, *Gaussian*, *Radial Basis Functions (RBF)*, and *hyperbolic tangent* *(Bishop, 2006)*.

Its behavior is, moreover, conditioned by the type of *kernel* used and the values given to its parameters. The core of an *SVM* is a definitive-positive symmetric function that allows the data to be projected into a large-sized transformed space in which class separation is more easily performed, in the same way as the hidden neurons of an *MLP* allow to project the input data into a representation space in which the weights of the output layer define linear discriminant functions of the classes. The values of the kernel parameters directly affect the complexity of the decision boundary of the classifier. More detailed descriptions of *SVM classification* and *regression algorithms* can be found in *(Schölkopf, Smola, 2002)*.

Recently *SVM* which was developed by *(Cortes, Vapnik, 1995)* is one of the methods that are receiving increasing attention with remarkable results.

Recently *SVM* is one of the methods that are receiving increasing attention with remarkable results. Many studies have demonstrated the superiority of *SVM* over conventional discriminant methods such as *MLPs*, *Fisher discriminant*, *RBF networks*, and *so on*. Modified versions of the *SVM* allow the best performance on several standard databases. Implementations of *SVMs* (*e.g.*, *SCIKIT-Learn* *(Pedregosa et al., 2011)* have several ways to transform a problem into a linearly separable one with the use of *kernels* (*polynomial*, *RBF*, *etc*.). Furthermore, *SVM* take the advantage of using *NL kernels* to map the data to a very high dimensional space. For example, it was shown in *(Alzghoul, Lofstrand, 2011)* that the one-class *SVM* outperformed the polygon-based and grid-based methods because it maps the data into a higher dimension.

Since *SVM* was proposed by *Vladimir Vapnik*, it has aroused the interest of several research communities from different areas of expertise and has become more and more popular in various application domains, due to its great modeling abilities in *linear/NL data classification* and *regression*. Compared to other widely used *supervised learning* methods such as *NNs*, *SVM* may have high *accuracy* and better *generalizations* capability under many cases. Due to these capabilities, *SVM* has also gained lots of successful applications in *process industry*, in terms of *FM*, *fault classification*, *CM* *(Kusiak, Li, 2011; Ibrahim et al., 2016)*, *soft sensor developments*, *predictions* and for complex data sets in general *(Géron, 2019)*.

(Zhang, 2008) proposed an *FDD method* for *NL* processes based on *Kernel Independent Component Analysis (KICA)* and *SVM*. *(Tian et al., 2015)* applied *SVM* for *FDi* in steel plants. *(Xiao et al., 2014)* designed two methods for selecting Gaussian kernel parameters in one-class *SVM* and made an application to *FDe*. *SVM* was used for monitoring continuous decision function in *incipient FDi* by *(Namdari, Jazayeri-Rad, 2014)*. *(Saidi et al., 2015)* applied higher order spectral features in *SVM* modeling and used it for bearing *faults classification*. *(Jing, Hou, 2015)* developed *PCA* and *SVM* based *fault classification* approaches for complicated industrial processes. *(Wu et al., 2014)* carried out *FDD* in process data by using *SVM*. Furthermore, *SVM* classifier was applied to cables and

transmission lines for line *FDi* and localization *(Dash et al., 2007; Parikh et al., 2010)* using a model-based approach.

Nearest neighbors' algorithm also known as *K-NN*, is a simple non-parametric method in *ML*, which can be used for both classification and regression *(Altman, 1992).* In both cases, the input consists of the *k* closest training samples in the feature space. The output depends on whether the method is used for classification or regression. For data classification, the output is a class membership. A data sample is classified by a majority vote of its neighbors. If *k* is selected as 1, the output of the data sample will simply be assigned to the class of its nearest neighbor. For data regression, the output is a continuous value for the data sample. Normally, the output value for the predicted data sample is determined through averaging the values of its k nearest neighbors. In this method, the model structure is totally open to any type. For both classification and regression, *NN* or *k-NN* has been considered as one of the simplest methods of *ML* algorithms.

In the past years, like other supervised *ML* algorithms, *NN* or *k-NN* has also been used for various applications in the process industry, *e.g.,* process monitoring, fault classification and soft sensor development. *(He, Wang, 2011)* developed a statistical pattern analysis and process monitoring method based on the nearest neighbor method, and applied it in Semiconductor Batch Processes; *(Penedo et al., 2012)* carried out hybrid incremental modeling based on least squares and *fuzzy K-NN* for monitoring tool wear in turning processes.

Decision support tool that uses a tree-like graph or model to describe relationships among different variables and makes decisions. *DTs* are commonly used in operations research, particularly in *decision analysis*, in order to help identify a strategy that most likely to reach the aim *(Quinlan, 1993).* Recently, *DT* has also been introduced into the process industry.

The most common applications have been made in process monitoring, *FDi*, and quality prediction. *(Kuo, Lin 2010)* used *NN* and *DT* for prediction of machine reliability; *(Yeh et al., 2011)* used the decision algorithm to extract classification knowledge in mold tooling test; A *fuzzy DT* method was proposed by *(Zio et al., 2009)* for fault classification in the steam generator of a *PWR*; *(Ma, Wang, 2009)* carried out inductive data mining based on genetic programming for automatic generation of *DTs* from data, and used it for process historical data analysis; *(He et al., 2013)* applied the *DT* learning technique for online monitoring and *FId* of mean shifts in bivariate processes; *(Demetgul, 2013)* proposed a *FDi* method for production system with *SVM* and *DTs* algorithms; An approach for automated *FDi* based on a *fuzzy DT* and boundary analysis of a reconstructed phase space has been proposed by *(Aydin et al., 2014).*

III.5.4 - Unsupervised Learning Methods

The main goal of the *unsupervised learning method* is to explore the data and find some *hidden structure* among them. Furthermore, *unsupervised learning* is used to discover groups of similar examples within the data which is called *clustering*, or to determine the *distribution of data within the input space*, known as *density estimation*, or to project the data from a *high-dimensional space* down to *low dimensional space* for the purpose of *dimensionality reduction* and *data visualization*. For *industry applications*, this type of *ML methods* is mainly used for *dimensionality reduction*, *information extraction*, *data visualization*, *density estimation*, *outlier detection*, *process monitoring*, *etc.* Conventionally applied *unsupervised learning methods* in the process industry include *PCA*, *Independent Component Analysis (ICA)*, *k-means clustering*, *Kernel Density Estimation* (*KDE*), *SOM*, *manifold learning, Support Vector Data Description (SVDD)* and *so on*.

K-means clustering is a method of vector quantization, which was *originally developed* for *SP (Lloyd, 1982).* It is one of the simplest and popular *unsupervised ML* and the most known among the regrouping methods *(MacQueen, 1967)* that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume *k* clusters) fixed a priori. The main applications of this method in the process industry are for dividing the process data into various operating modes, different fault types, or different grades of products. Kernel *k-means clustering* based local support vector domain description method has been developed for *FDe* of multimodal processes *(Khediri et al., 2012)* used the k-mean clustering algorithm for monitoring the offshore pipeline; *(Zhou et al., 2012)* combined the *k-means clustering* method and the *PCA* method for *FDid* in multiples processes; *(Tong et al., 2013)* developed an adaptive multimode process monitoring strategy based on the *k-means clustering* algorithm.

KDE is a *non-parametric* way to estimate the probability density function of a random variable. In cases where the distributions of the data are not known which are usually non-Gaussian, the *KDE* is used as a fundamental data smoothing method which can provide an inference about the population, given a finite number of training data samples *(Wand, Jones, 1995).* In the process industry, the *KDE* method has been used for estimating the distributions of process variables, monitoring statistics, or other related quantities that are used for describing the nature of the process.

KDE method is applied in the process industry. *(Chen et al., 2004)* proposed a regularized *KDE* method for clustered process data; Jiang and Yan *(Jiang, Yan, 2013)* used the *KDE* approach in the weighted kernel *PCA* model for monitoring *NL* chemical processes; *(He et al., 2013)* applied the *KDE* method for estimating the distribution of the froth color texture, in order to monitor the Sulphur flotation process; a *control-loop diagnosis* approach has been developed by continuous evidence through *KDE (Gonzalez, Huang, 2014); KDE* was combined with the nearest neighbor method for process *FDe (Wang et al., 2013);* in the PCA-based control chart application, *KDE* has been used for multivariate non-normal distribution estimation. *(Phaladiganon et al., 2013*; *Gonzalez et al., 2015* combined *KDE* with Bayesian networking for process monitoring.

GMM is a probabilistic model for representing the presence of subpopulations within an overall population, without requiring that an observed data set should identify the sub-population to which an individual observation belongs *(Bishop, 2006).* For those processes which have multiple operating modes or aim to produce multiple grades of products, the *GMM* is particularly useful to characterize those multi-modal data natures. Besides, the *GMM* would also be helpful in those processes which have highly *NL* relationships among process variables, or the distributions of some process variables are non-Gaussian. In those cases, the *GMM* serves as local linearization or local Gaussianity tools for data descriptions, based on which basic linear or Gaussian sub-models can then be developed for further data mining and analytics.

Similarly, *GMM* can also be used for general process applications, such as data clustering analysis, process monitoring, dimensionality reduction, data visualization, *etc*.

(Choi et al., 2004) used a *GMM* via *PCA* and discriminant analysis for process monitoring. *(Yu, Qin, 2008)* proposed a multimode process monitoring scheme based on Bayesian inference with finite *GMM*s; *(Chen, Zhang, 2010)* used the *GMM* for online multivariate statistical monitoring of batch processes; *(Yu, 2012)* proposed a *GMM* and Bayesian method to incorporate both local and nonlocal information for monitoring the semiconductor manufacturing process; *(Zhu et al., 2014a)* developed a robust mixture model for process monitoring; *(Wen et al., 2015)* combined the *GMM* with the canonical variate analysis method for monitoring dynamic multimode processes; *(Yan et al., 2014)* developed a semi-supervised mixture model for discriminant monitoring of batch processes; *(Yu, 2012)* developed a particle filter driven dynamic *GMM* for monitoring of complex processes; *(Liu, Chen, 2010)* employed the *GMM* to extract a series of operating modes from the historical process data, and then formulated a nonstationary *FDD* method for multimode processes; *(Feital et al., 2013)* discussed the application of *GMM* for Modeling and Performance Monitoring of Multivariate Multimodal Processes; *(Yu et al., 2013)* combined the *GMM* with multiway *ICA* for *FDD* of multiphase batch processes.

For dimensionality reduction of high-dimensional data for the process industry, the manifold learning method has recently been introduced. High-dimensional data requires more than two or three dimensions to

represent, which is practically difficult to interpret. One approach to simplification is to assume that the data of interest lie on an embedded *NL* manifold within the higher-dimensional space *(Lee, Verleysen, 2007).* If the manifold is of low enough dimension, the data can be visualized in the low-dimensional space.
Conventionally used manifold learning methods include principal curves, generative topographic mapping, Gaussian process latent variable model, maximum variance unfolding, isomap, locally linear embedding, Laplacian Eigen maps, diffusion maps, neighborhood preserving embedding, locality preserving projections, *etc*. Based on the *NL* dimensionality reduction procedure provided by the manifold learning method, further data analytics can be carried out, such as process monitoring, *FDD*, soft sensor modeling and applications, and so on.

The method of *SVDD* is similar to one-class *SVM*, based on which the boundary of a dataset can be used to detect novel data or outliers *(Tax, Duin, 2004). SVDD* obtains a spherically shaped boundary around a dataset, which defines a region for description of normal data samples. By introducing the kernel trick, the *SVDD* method can be made flexible to use various kernel functions and thus is able to describe highly *NL* data. The main features of the *SVDD* method are demonstrated in *Figure III.20*.
According to the feature of the *SVDD* method, it can be used for novel detection, outlier detection, monitoring abnormality of data, *etc*. Along the past years, the *SVDD* method has been introduced into the process industry, and lots of applications of this method have been reported.

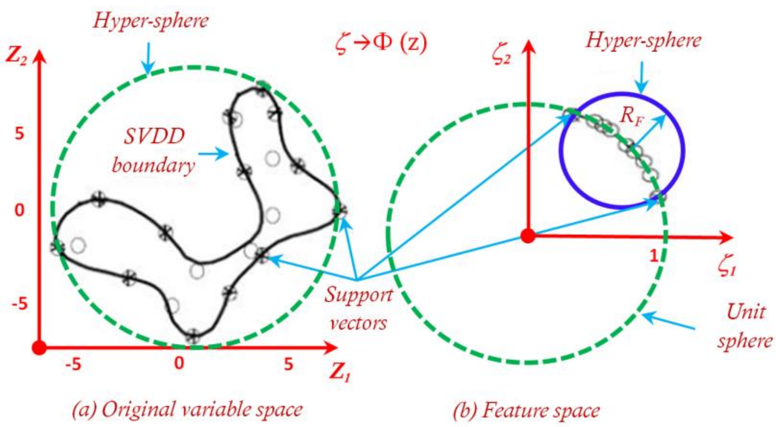


Figure III.20 - Illustration of SVDD method (Liu et al., 2008).

Later, a new non-Gaussian fault reconstruction method has been formulated upon the SVDD model, which can be used for sensor *FId* and isolation in the process industry *(Ge et al., 2009). (Ge et al., 2011)* extended the application of *SVDD* for batch process monitoring, and later boosted its performance by introducing the bagging strategy *(Ge, Song, 2013). (Liu et al., 2011)* improved the *NL PCA* method with introduction of the *SVDD* model, and applied it for process monitoring. *(Zhu et al., 2011)* developed a multiclass *SVDD* model and combined it with a dynamic ensemble clustering method for transition process modeling and monitoring. *(Jiang, Yan, 2014)* proposed a probabilistic weighted *NPE-SVDD* method for process monitoring. *(Yao et al., 2014)* developed a batch process monitoring based on functional data analysis and *SVDD*. *(Du et al., 2014* developed a monitoring scheme based on lazy learning, *SVDD*, and modified receptor density algorithm, and used it in *NL* multiple modes processes.

III.5.5 - Semi-Supervised Learning Methods

For applications in the process industry, the semi-supervised learning method is particularly useful when the cost of labeling data samples is expensive or time consuming. Compared to unsupervised and supervised learning, the application of semi-supervised learning has not received too much attention in the process industry until in the recent several years. Represented semi-supervised learning schemes include generative *MBT*, self-training, co-training, graph-based method, *etc*. *(Zhu, Song, 2010; Sumana et al., 2010).* There are already some semi-supervised application examples in both data classification and regression. *(Zhao, Gao, 2015)* proposed a semi-supervised Bayesian method for soft sensor development, which can successfully incorporate the information from unlabeled data. *(Zhong et al., 2014* proposed a semi-supervised *FiDiAn* model for fault classification in industrial processes. *(Yan et al., 2014)* proposed a semi-supervised mixture discriminant monitoring method for batch processes. *(Zhou et al., 2015)* proposed a semi-supervised PLVR models for process monitoring with unequal sample sizes of process variables and quality variables. *(Zhu et al., 2015)* proposed a robust form of mixture semi-supervised *PCR* model for soft sensor applications. *(Bao et al., 2015)* combined the co-training strategy with *PLS* for development of a semi-supervised soft sensor.

III.5.6 - Steps

The *ML* process can be represented as a series of *steps* composed of *data acquisition* and *preprocessing* as shown on *Figure III.21*, where possibly different data sets and modalities are integrated, cleaned of outliers, *etc*. (*a*) *Feature selection and extraction*: important signals and characteristics are identified and extracted from the data. (*b*) *Model selection*: an appropriate model is chosen, taking into consideration the task to be solved. (*c*) *Validation*: a performance measure is used that is specific to the task, including *accuracy* (classification) and *Mean Absolute Error* (*MeAE*) (*regression*), evaluated on a validation set of data.

Figure III.21 - General structure of ML System.

A *FM* system may rely on several types of datasets. Most *FM* models discussed in the literature are based on operational and event datasets, such as the ones provided by *SCADA*. *SCADA* systems generally provide, by time-series signals in regular intervals. This type of system collects basic information with the use of sensors (*e.g.,* bearing vibration, temperature, phase currents, wind speed, *etc*.). There is no common set of available *SCADA* signals nor is there a generally accepted taxonomy of signals, with different systems having different names.

Data collection and preparation is the first and crucial step in developing a predictive model. Data preparation is an indispensable step in order to convert various data forms and types into proper format that is meaningful to *ML* predictive model. During the system operation, larger amounts of data are collected during processing on a regular basis. The collected data comprise all the variables including the predictor variables that can be used for establishment of prediction models operating conditions.

As well as *SCADA* time series signals, different other types of data might be collected such as drone images or event data in *text-free* form.

Data cleansing phase is an important phase in predictive modeling for anomalies which consist to obtain a complete cleansed data set that can be modeled with outliers removed and solutions for handling of missing data applied. Missing values were substituted with the class mean.

Also, the extracted data should be normalized for all the range of values of raw data varies widely. To normalize a data set, the continuous variables were transformed on a linear scale to a value with a range of 0 to 1 or -1 to

1. Ordinal data were spaced equally over the same range. In order to normalize the raw data of input and output the following normalization equation is used:

$$x_{norm} = 2x\frac{(x-x_{min})}{(x_{max}-x_{min})} - 1 \quad \text{(III. 7)}$$

where x is the data to be normalized, *i.e.,* and x min and x max are minimum and maximum values of the raw data. In such a way, all the inputs and the desired outputs are normalized within the range of ± 1.

One of the major challenges in process is that the number of tool *variables* is usually very *high*; in such setting, *variable selection techniques* often prove to be useful *(Gallo et al., 2007).* Feature selection is the process of *selecting variables the most influential* that we wish to *study*, *understand* or *predict*. This can be achieved under the guidance of an expert. This step is the most important in the whole process of predictive modeling because the success of any predictive model is largely depending on the predictor variables that are selected to use as *inputs* for the *model*.

Feature extraction is used to *compress high-dimensional* time series (such as sensor signals) by keeping their main characteristics intact while discarding noise and removing correlations. This should speed up model training and produce better outcomes than when applied to the original, dataset. Several techniques of *feature extraction* can be used, such as (*a*) *statistical indicators (Anker et al., 2003),* is the simplest to compute and sometimes the most efficient; these include *mean*, *standard deviation*, *maximum*, *minimum*, *skewness*, *kurtosis*, *peak-to-peak, crest factor*, *wave factor*, *impulse factor*, *margin factor*, *root mean square*, *etc*. *(Kateris et al., 2014)* (*b*) *Time-frequency domain* include the largest coefficients of the *Discrete Fourier/ WT (Mörchen, 2003), Haar WTs (Subramani et al., 2006), etc*. (*c*) *Parameters of fitted time series models* such as *coefficients of fitted ARIMA models (Box et al., 1994), etc*.

The *ML model* selection step is particularly significant as it is the core functionality that learns from past data and generalizes into the future. Such models have been used for different tasks, including classification, regression, anomaly detection, synthesis and sampling, imputation of missing values, de-noising, density estimation and many others *(Goodfellow et al., 2016).*

Validity of *ML* models can be estimated through several specific measures in combination with an out-of-sample technique such as n-fold cross validation which assess how well the results of the model will generalize beyond the training data.

III.5.6 - Advantages and Drawbacks

DD FM methods are well suited for complex highly *NL* and large-scale systems. They can save time and cost since they do not require understanding of the physics of the system being modeled; they are *model-free (Chiang et al., 2001; Ng et al., 2001; Alzghoul et al., 2014).* So, *DDTs* are preferred when the product data is available while the system model is not *(Sankavaram et al., 2009).* An *additional benefit* of *DDTs* is the *detection of unknown faults* via outlier detection. *DDTs* may be applied for *prognostics* as well, *i.e.,* predicting the time at which a system or a component will no longer perform its intended function. However, they mainly require large set of data for training for both normal and faulty operations, and depend on the quantity and the quality of data *(Chiang et al., 2001; Ng et al., 2001).* This brings out a crucial point of distinction between approaches based on historical process data and model-based approaches.

III.6 - Knowledge-Based Methods

The *knowledge-based tools* are popularly used for *FM*. These tools are mainly built on the expert opinion and using if-else-then logics *(Venkatasubramanian et al., 2003a; Chih-Min, Yun-Pei, 2008). KBTs (Nomikos, MacGregor, 1995)* typically mimic the behavior of a human expert. They are based on *qualitative models* and their performances are based on the quantity and quality of knowledge of a specific domain.
KBTs are suitable when the representation mode of the knowledge is of symbolic type, the detailed *MM* is not available, and when the number of inputs, outputs and states of a system is relatively small *(Chiang et al., 2001; Ng et al., 2001).* Furthermore, when obtained information is incomplete or uncertain in nonlinear, complex systems, it is essential to deal with the incomplete *knowledge* in an efficient way. Therefore, a more suitable solution to process incomplete *knowledge* may be the utilization of *KBTs (Kiliç, 2005).* In practice, it is demonstrated that, in that case, human operator can supply a better supervision by using his own knowledge and his experience to insure a good process operation *(Fragkoulis, 2008).*

The requirements for a knowledge representation include: (*a*) it should be able to describe the precedence information, (*b*) potential process faults should be included as complete as possible, and (*c*) the *CE* relationships between process faults and affected quality variables should be expressed explicitly.
(Alzghoul et al., 2014) define five requirements for *KBT*: *(a)* sensor data to tune the *KBT* parameters *(b)* a known data-label for model verification (*i.e.,* our knowledge regarding when faults appear and disappear). *(c)* good system knowledge *(d)* knowledge regarding normal and abnormal behavior among the various monitored system parameters *(e)* that the technical system allows for formulating the continuous queries (*i.e.,* ''*rules*''; therefore, too complex systems may need to be simplified.

KBTs can be applied in *FDe* and all phases of *FDi*. *KBTs* use *qualitative models* in *FDD* process *(Chiang et al., 2001; Ng et al., 2001)*. *Knowledge-based FDi* is performed based on the evaluation of on-line monitored data according to a set of rules which the human expert has earned from past experience *(Monsef et al., 1997). KBTs* can be usually obtained through *causal modeling* or *detailed description of systems*, *expert knowledge*, or typical *fault symptoms (Chiang et al., 2001; Ng et al., 2001).*
The role of the knowledge-based approach in process supervision and monitoring is to provide some interesting solutions for the supervision problems. It is necessary to consider this approach not as a substitution of the traditional methods, but as a supplementary tool for an engineer who has to find a solution to a specific problem.

The role of the knowledge-based approach for *FM* can be considered from several points of view *(Gentil, 1996)* : (*a*) *declarative:* the implementation of several reasoning strategies (prediction, *FDi*, *etc.*) is permitted and is not based on the existing knowledge; (*b*) *explicative*: the man-machine co-operation is enhanced, using causal reasoning as a base for *diagnosis* and *explanations*; (*a*) *management of different types of data*: imprecise (measurement noise), incomplete (sensor faults), non-homogenous (logical and analogical data), dependent of the context, temporal, *etc*. These data are used in order to include in the system all the available information, even the heuristic one.
FDi for technical systems and processes *need experiential knowledge* in parallel to *scientific knowledge* for the effective solution of the *FDi* problem-solving process. *Different FDi approaches require different kinds of knowledge* about the process. These *approaches include first principal knowledge* governing the process operation, *empirical knowledge* such as operators' experiences and *historical data* about the process operation under various *normal* and *faulty conditions*. Furthermore, the *knowledge includes* the *locations of input and output process variables*, *patterns of abnormal process conditions*, *fault symptom*, operational constraints, and performance criteria. The operator and engineer's intelligence related to the specific process systems has a major importance. Their knowledge can help to recognize the potential faults based on previous experiences. This approach can reduce the burdens on exact numeric information and automates the human intelligence for process supervision *(Lo et al., 2006).*

The *knowledge-based* procedures can consist of an existing *expert knowledge*, an *inference engine*, or an *ES* interface which can combine with the *knowledge* from *first principles* or *structural* description of the *system* in terms of *rules* *(Yu et al., 2014).* The *FDi methodology* is *comprised* of *three steps*. The *first step* is *acquiring* the real-time process *information*, from critical equipment, such as boilers, compressors, separators or reactors. Temperature, pressure, level, and *FR* are the most important process variables to be monitored and have the capability of representing the state of operation in a variety of equipment. The fault in these variables can affect the stability and safety of the whole process system. The *second step* is *making inferences* based on acquired process information. The *last step* is *making actions* according to the inference values, such as informing operators, raising alarms, shutting down equipment, activating higher layer protections and trying to bring the system back to normal condition.

The schematic diagram of knowledge-based *FM* is depicted by *Figure III.22* *(Gao, 2015b).*

Before implementing the *KBT* *(Isermann, 2011),* extensive data collection such as technical specifications and schemes should be performed and analyzed for system understanding *(Miles, Huberman, 1994).* Process data contains valuable information about the state, operation, and behavior of the process plant, more so in case with limited available process knowledge *(Dash et al., 2004).* Interviews and workshops representatives should conduct to elicit common faults affecting system reliability *(Yin, 2008).* Further information regarding the data collection and analysis for the *KBT* can be found in *(Löfstrand et al., 2012)*.

(Nan et al., 2008) proposed a *knowledge-based FM* method, which uses the valuable *knowledge* from *experts* and *operators*, as well as real-time data from a variety of sensors.

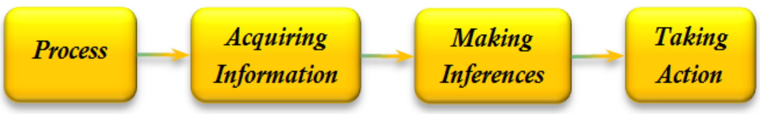


Figure III.22 - Steps of KBTs for FM.

Knowledge-based FDe is constructed by analytical and heuristic symptom (event) generation. The features from system characteristic values (*variances*, *amplitude*, *frequency*, *model parameters*, *state variables*, *transformed residuals*, *special noise*, and *vibration*) are extracted, while the system is working under normal and faulty conditions using analytic and heuristic knowledge. Then the features containing faults are compared with the features of the non-faulty process and methods of change detection are applied. The features related to the system behavior are extracted from system characteristic values. The features related to the system behavior are extracted from system characteristic values *(Kiliç, 2005).*

The objective of this step is to guide the process back to normal in the case of abnormal conditions. After detecting an abnormal event, which could cause severe accidents, the proper actions are required immediately. This will be achieved by developing a set of actions which include activating safety measures and a higher layer of protection.

The most popular knowledge-based *FDD* tools including *FTA*, *expert systems (ES), signed direct digraph (SDG), CE graph*, *BN, etc*. The main feature of this family of approaches is that knowledge used here is obtained empirically. A survey of *knowledge-based FM* methods was performed by *(Zhu, Yu, 2002; Venkatasubramanian et al., 2003c*.

The *extraction* process of the *knowledge* base may be either *qualitative* or *quantitative*. It also shows that *KBTs* can be either *model-qualitative-based* (such as *causal models*) or *qualitative data-based* (such as *ESs*). *Quantitative information* (or *features*) can be either extracted by using *statistical* or *non-statistical* (*e.g., NNs*) *methods*. Therefore, the *quantitative knowledge-based FM* can be roughly *classified* into *statistical analysis-based FDi* and *non-statistical analysis-based FM*.

III.6.1 - Model-Qualitative-Based Method

Applying a variety of *AI* techniques (either symbolic intelligence or computing intelligence) to the available historic data of the industrial processes, the underlying knowledge, implicitly representing the dependency of the systems *features*, can be extracted. The consistency between the observed behavior of the operating system and the knowledge base are then checked, leading to a *FDi* decision with the aid of classifier.

Qualitative model is derived from a fuzzy model using the linguistic approximation method. Therefore, *qualitative model* is a generalized fuzzy model consisting of *linguistic explanations* about system behavior. A linguistic model is a model that is described or expressed using *linguistic terms* instead of mathematical equations with numerical values or conventional logical formula with logical symbols. *Linguistic terms* in linguistic explanations are found such that they linguistically approximate the fuzzy sets in an underlying fuzzy model. *MQlBM* utilizes a model where the *input-output relationship* of the plant is expressed in terms of qualitative functions centered on different units in the process. *MQlBM* is broadly classified *into abstraction hierarchy*, *FTrs*, *diagraphs* and *fuzzy systems*.

Conversely to *quantitative models*, *qualitative* are limited to reproducing observed behavior without particular knowledge of the process. These models are implemented by using *qualitative equations*, *models based on fuzzy sets*, *rules*, *description of behavior*, *etc*. *Differences* between *knowledge-based systems* and *other techniques*: In mathematics, control theory and computer, trying to solve the problem through its modeling (model problem). In an expert system the problem is attacked by building a model of "expert" or problem solver (expert model); in the Alarm Management with *FDi* the human knowledge will be so important for defining the Failure mode of the equipment to analyze. It is worthy to point out *model-based diagnosis methods*, *signal-based diagnosis approaches* and *knowledge-based diagnosis* algorithms all have to utilize real-time data when doing real-time monitoring and on-line *FDi*, however, only knowledge-based diagnosis approaches need to employ a large volume of historic data available. From this point of view, *knowledge-based FDi* is also referred to *data-driven FDi*.

For the *sources*, *i.e.*, *information* or *data*, for *qualitative modeling*, we find the following *classification* of the sources: (*a*) conventional *MMs*; (*b*) observation based on knowledge and/or experience; (*c*) numerical data; (*d*) image data; and (*e*) linguistic data.

Among the most popular *qualitative methods*, let us mention: *qualitative differential equations* (Kuipers, 1986). *Influence/causals graphs* such as: *digraphs* (Gentil et al., 2004), *bond-graph* (Rocha-Loures, 2006). (Zhang, Jiang, 2008) classified the *qualitative methods* used in *model-based* for redundancy as *causal models* such as *structural graphs*, *FTrs*, *quantitative physics*; and *abstraction hierarchy* which can be *structural* or *functional* as shown by *Figure III.23.*

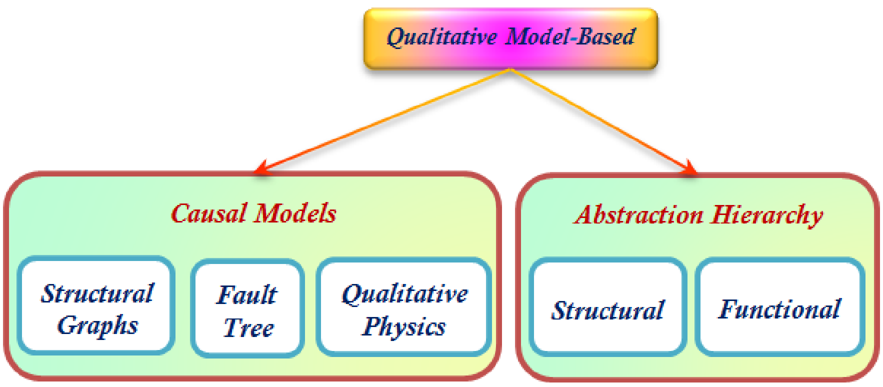


Figure III.23 - Classification of qualitative methods used in model-based.

(Sugeno, Yasukawa, 1993) divide methods of qualitative modeling into two parts: fuzzy modeling and linguistic approximation. According to *(Sztyber, 2015),* the most popular qualitative models in *FDi* are: structural models; *BG*s; and *Causal Graphs (CGs)*.

III.6.2 - Expert System

A distinct *symptom-cause* linkage can be expressed without any deep knowledge of the systems' structure, function or principles of operation. The use of this compiled, shallow knowledge of a *FDi* expert in the form of heuristic rules has been shown to provide good results in domain areas where the underlying knowledge of the symptom-cause linkage is not clearly defined, or where an adequate model of the system to be diagnosed is not readily available, such as in the field of medicine *(Becraft, Lee, 1993).*

In the late 1960's to early 1970's, *ES*s began to emerge as a branch of *AI*. The first diagnostic *ES*s for technical *FDi* were developed in the early 1970's at MIT as is reported by *(Saludes et al., 2003).* From the early stage, when *(Barr, Feigenbaum, 1981a, Barr, Feigenbaum, 1981b)* published the reference for the early *ES*s, numerous systems have been built in a variety of domains. Early diagnostic *ES*s were rule-based and used empirical reasoning whereas new model-based *ES*s use functional reasoning. Since then numerous systems have been built. Surveys of the first diagnostic *ESs* of technological processes are provided by *(Saludes et al., 2003).*
During the period 1985-1995 *ES*s were the "hot topics" in *AI* developments due to the attention in knowledge management issue. After 1995 *ES* applications started to decline as stand-alone systems and their technology embedded in mainstream of information technology. New *ES*s started to combine symbolic with numerical information or with other *AI* techniques to produce more effective systems.

One of the most known *qualitative FDi* methods is *expert system-based method*.
ESs are system based on a set of rules presenting human's expertise *(Angeli, Chatzinkolaou, 2004; Dai, Gao, 2013)* by using a symbolic representation of the human knowledge. *ESs* are powerful tools that use *AI* techniques for providing information just like a human expert would. *ESs* are intelligent computer-based applications that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution.
ESs are used to imitate the reasoning of human expert when used in diagnosing faults.
The experience from an expert can be combined with the knowledge from first principles or a structural description of the system for diagnosing faults. *ESs* are able to capture human *FDi* associations that are not readily translated into mathematical or causal models.

Meanwhile, an *ES*s approach can be classified into: (*a*) *shallow-knowledge ESs* using the formulation of *if-then* rules for generating rule-based methods; (*b*) *deep-knowledge ESs* including functional reasoning or first-principles *ES*s for diagnosing faults and (*c*) *ML methods (Yu et al., 2014). Rule-based ESs* has been investigated very intensively for *FDD* problems *(Patton et al., 1989).*

Expert system-based FDi was initialized in 1980s *(Henley, 1984; Chester et al., 1984),* which was performed based on the evaluation of on-line monitored data in terms of a set of rules, learned by the human experts from past experience.
Advanced software applications, based on the *ES*, has the potential to assist engineers in monitoring, detecting, and diagnosing abnormal conditions and thus providing safe guards against these unexpected process conditions.
On-line diagnostic *ES*s usually use a *combination* of *quantitative* and *qualitative methods* for *FDe* that allows interaction and evaluation of all available information sources and knowledge about the technical process. In

these systems although basic *FDi* procedures are very satisfactory, real-time issue such as sensors drift can lead to problems with nuisance alarms in a system.

Usually, the main components in the *ES* development include knowledge acquisition, choice of knowledge representation, the coding of knowledge in a knowledge base, the development of inference procedures for *FDi* reasoning and the development of input-output interfaces.

According to *(Kempowsky, 2004), ES* is composed of *two* independent parts: *knowledge base* and *inference engine,* as is shown on *Figure III.24.*

The *first part* is in turn composed of *rule base* which models the knowledge of the considered domain and *fact base* which contains the information of the treated case. The *second part* is able to reason from information contained in the *knowledge base, to make deduction*. As the data are applied, new facts are deducted and are added to the *fact base*.

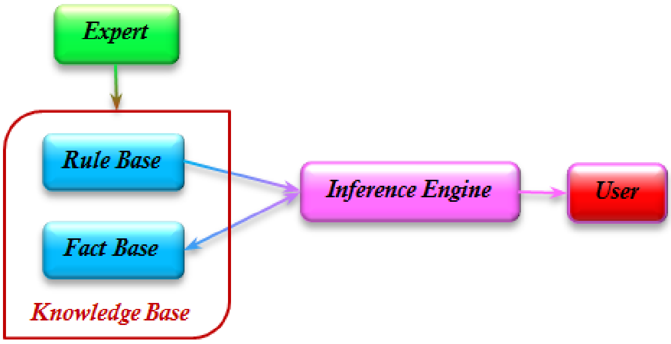


Figure III.24 - ES architecture (Kempowsky, 2004).

Numerous *ESs* have been developed for monitoring applications in a wide variety of domains, as catalogued by *(Waterman, 1986).* The *ES* approach for monitoring is intuitively attractive, as symptoms can be linked to causes explicitly, in a rule-based knowledge representation scheme *(Becraft, Lee, 1993).* Owing to the advantages, *ES*-based *FM* methods received much attention particularly in 1980s and 1990s, which have been successfully applied to a variety of engineering systems such as gas turbine combustion chambers *(Afgan et al., 2006), boiler feed water systems (Adamson, 1990),* energy systems *(Toffolo, Lazzaretto, 2008),* chemical processes *(Nan et al., 2008), turbo-generators (McDonald et al., 1991), refrigeration process of a hydraulic power plant (Berrios et al., 2008),* and vehicles *(Mostafa et al., 2012), etc.*

(Angeli, Atherton, 2001) developed an on-line expert system to detect faults in electro-hydraulic systems using on line connections with sensors, signal analysis methods, model-based strategies and deep reasoning techniques. Expert knowledge is contained primarily in a model of the expert domain. The final *FDi* conclusions are conducted after interaction among various sources of information.

(Saludes et al., 2003) reported a *FDIso* scheme for hydroelectric power stations based on a *NN* and expert system subsystems. The expert system stores knowledge acquired by operators for the *FDi* conclusions while the *NN* has been trained with data automatically collected for one year in order to decide between normal and abnormal states. This system was in the implementation state at the time of the report. *(Yu et al., 2008)* presented the development and implementation of an expert system for real time *FDi* in chemical processes that provides suggestion to the operator when abnormal situations occur. Industrial applications to the fluid catalytic cracking process in refinery are also presented.

(Nabeshima et al., 2003) reported an on-line expert system for *NPPs* that uses a combination of *NN*s and an expert system in order to monitor and diagnose the system status. The expert system uses the outputs of the *NN*s generated from the measured plant signals as well as a priori knowledge base from the *PWR*. The electric power coefficient is simultaneously monitored from the measured reactive and active power signals. *(Biagetti, Sciubba, 2004)* depicted a description of an expert system capable of monitoring the performance of a cogeneration plant.

Though the approaches are simple both of them consider limited number of faults and the cases of multiple faults are not included. *(Yusong, Pung et al., 2006)* have described the architecture of an expert system for *FDi* in a hydraulic brake system where the acquired knowledge for the knowledge base is based on software simulation. This simulation-based knowledge generation in combination with fuzzy knowledge representation is used for the final *FDi* reasoning. A *task-based diagnosis expert system* was proposed in *(Ma et al., 2012)* recently, where object-oriented knowledge representation methods were utilized so that the rules of a specific machine can be customized flexibly on the basis of general rules. In *(Kodavade, Apte, 2012),* a universal *FDi* expert system framework was presented, where the object-oriented paradigm and rule-based expert system were integrated, providing a flexible and powerful environment for *FDi* process.

Some of the advantages in the development of *ESs* for monitoring solving are ease of development, transparent reasoning, the ability to reason under uncertainty and the ability to provide explanations for the solutions provided. Nevertheless, *FM* using rule-based *ES*s needs an extensive database of rules (sometimes difficult to acquire), and the accuracy of *FDi* depends on these rules. Creating a rich and detailed database of rules is usually a time-consuming task and many process experts are needed. The main weaknesses are that they are very specific to a system, hence the updating or change of rules and the uniqueness of knowledge are problems when large industrial plants are considered for these require large amount of effort. Furthermore, the limitations of *rule-based ESs* are revealed when they are confronted with novel fault situations for which no specific rules exist. If the knowledge base does not contain the necessary information about a particular fault situation, the *ES* will fail and be unable to diagnose the fault. Also, within the knowledge-based concept, the lack of a founded, tried and tested theory is a problem.
More advantages and disadvantages of *ES*s technology regarding the *FDi* processes for technical systems are given by *(Widman et al., 1989).*

III.6.3 - Fuzzy System

Fuzzy systems use the concepts of the fuzzy set and *FL* theory, introduced by *Zadeh* in the early 1960's. A fuzzy model considered as *qualitative models* is a representation of system characteristics by means of fuzzy rules which describe its behavior. The purpose is to generalize the information imitating the approximate reasoning executed by the man by introducing inaccuracy. In systems based on fuzzy rules, relations between variable are represented by means of fuzzy rules under the form: *If* premise *Then* conclusion. Decision in *FL* is based on the notion of expertise, which allows quantifying the fuzzy from a priori knowledge or acquired before. *FL* is another class of *CI* group, was designed originally to describe vague linguistic concepts. Block diagram of *FL* controller is shown in *Figure III.25 (Azar, 2010).*
Inputs to a controller pass through the fuzzification process using membership functions. The membership function is a graphical representation of the magnitude of participation of each input. The shape of some membership functions. All rules are evaluated in parallel using fuzzy reasoning. The process of *fuzzy inference* use membership functions. Converting the fuzzy information to crisp is known as de-fuzzification.

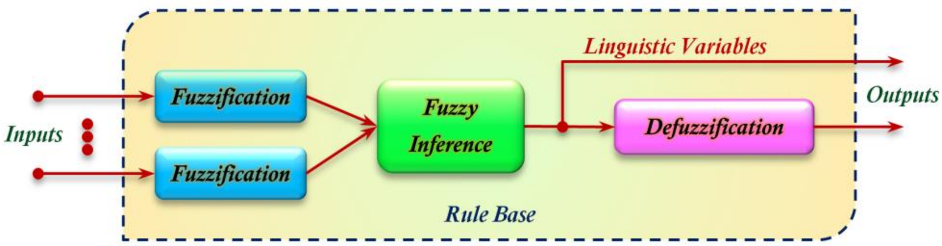


Figure III.25 - FL controller (Miljković, 2011).

Sometimes, the faults are detected by a model-plant mismatch. A possible solution to this problem was proposed in *(Schneider, Frank, 1994),* where an adaptation of a *FL* based threshold is used to detect faults in robots. Fuzzy FDI methods support in a natural way the direct integration of human operators in the *FDiso* process. This approach can be an important way of taking account of modeling uncertainty. Model-based fuzzy methods use the residuals generation to detect and isolate faults *(Isermann, 1998). (Dexter, Benouarets, 1997)* proposed the use of fuzzy reference models describing faulty and normal operation. The *FDi* is made by a classifier based on fuzzy matching.

Thus, *FDI* can benefit from *NL fuzzy modeling*. The use of fuzzy models increases the capability of *FDI* to work with systems without complete information and noisy. The key advantage of *FL* is that it enables the system behavior to be described by "*if-then*" relations *(Koscielny, Syfert, 2003).* The main trend in developing *fuzzy FDI* systems has been to generate residuals using either parameter estimation or observers, and allocate the decision making to a *FL* inference engine. By doing so, it has been possible to combine symbolic knowledge to quantitative information and, thereby, minimize the *FAl* rate.

Fuzzy systems are useful in any situation in which (*a*) there is no prior knowledge about fault-symptom causal relationship in the design of a *FDD* system; (*b*) the measurements taken are imprecise; (*c*) or their interpretation depends strongly on the context or on human opinion.

Similar to the *NN*s, fuzzy systems can be used either as residual generator or *PR* technique.

The application of *fuzzy* methods in *FDI* can be made in different ways. The use of expert knowledge in the form of a rule-based knowledge format is one of them *(Patton et al., 2000).* Another approach is presented in *(Mechefske, 1998),* where *FL* is used to classify the frequency spectra of various rolling element bearing with faults. *Fuzzy* sets can also be used to locate and identify the type of faults *(Insfran et al., 1999),* or for residual evaluation *(Frank, Koppen-Seliger, 1997b).* Industrial applications of *FL* in *FDI* can be found in *(Bartys, Syfert, 2002; Koscielny, Syfert, 2003).* The detection of faults can be performed by using *fuzzy decision making* (*FDM*), which avoids *FAl*s, as presented in *(Kuipel, Frank, 1997).*

The main difference between usage of *FL* in *model-based* and *history-based FM* is the type/method of fuzzy model/observer generation. In *model-based FM*, the fuzzy model is generated having some knowledge of the system behavior allowing the construction of the rule-base and selection of type and number of membership functions for each input/ output variable. In *history-based FM*, the fuzzy model is generated using observed input/output data. With input/output observation data, clustering techniques can be used to auto-generate a *fuzzy model*. *(Upadhyaya et al., 2003; Zhao, Upadhyaya, 2005)* examined the use of *adaptive fuzzy inference system* (*ANFIS*) for *FDe* in a *NPP*. *(Golmoradi, 2017)* proposed a *FIS* for monitoring the status of the compressor based on *Daubechies WT* and *DT*s.

The *advantage* of using *FL* is that it supports, in a natural way, the direct integration of the human operator into the *FDe* and supervision process using rules which are easy to understand. *FL methods* are rapidly becoming a powerful alternative to the use of *artificial ESs*. Sometimes the residuals in *fault-free* conditions are affected by the noise contamination and uncertainty effects. The consequence of this influence is the residual variation around the zero value, which can hide the faulty effects. The interesting capability to describing vague and imprecise facts and work with systems when the complete information is not available makes *FL* a powerful tool in this case. However, one drawback of fuzzy modeling is its complexity and time-consuming modeling procedure.

III.6.4 - Fault and Decision Tree Analysis, and Failure Modes and Effects Analysis

III.6.4.1 - Fault Tree

The *FTr*s, developed at the beginning of 1960's *(Villemeur, 1988).* They are symbolic logic models which describe all possible causes of a specified system state in terms of the state of the components within the system. They are used to quantify the likelihood of a system failure and for analysis of technological risk, to locate and to correct incidents. They can be used to prevent or to identify incidents before they happen, but they are used with more frequency in the analyses of reliability, availability and safety of systems, and to analyze accidents. When accident or a fault are happened, it can be identified the root cause of the negative event. They are deductive methods in which graphic representation of combinations is realized by an arborescent structure (tree), allowing a qualitative and quantitative treatment at the same time. This tree is established in the form of a logical diagram and contains in the summit undesirable event. The immediate causes which produce this event are then organized into a hierarchy by means of logical symbols "*And*" and "*Or*". In this way, the tree is created bit by bit to reach a set of events considered as elementary. The main drawback of *FTr*s is that the development is sensitive to errors at various stages. Indeed, the constructed tree is only as good as the mental model of the creator. To realize a correct *FDi* from the *FTr*s, these have widely to represent all the causal relations of the process, *i.e.*, that they must be capable of explaining all the scenarios of possible defects.
FTr can be achieved with the use of coherent and non-coherent *FTr*s. A coherent *FTr* is constructed from *AND* and *OR* logic, therefore only considers component failed states. The non-coherent method expands this allowing the use of *Not* logic which implies that the existence of component failed states and working states are both taken into account. Non-coherent *FTr*s to represent the causes of sensor outputs provide more reliable results compared with those obtained using the coherent *FTr*s.

*FTr*s offer the analyst comprehensive qualitative or quantitative analysis. Event trees allow the analyst to assess a system in both the success and failure domains. *(Papadopoulos, 2003)* has carried out work using state charts and *FTr*s to provide *continuous OLM* and rectification of systems. *Not* logic is excluded from the *FTr*s; therefore, only component failures are taken into account to obtain *FDi*. As a result, some faults occurring simultaneously have required conflicting remedial procedures. *(Yangping et al., 2000)* also developed a *FTr*-based method that only considers component failures, which uses *GAs* to continuously monitor for faults in *NPP*s. Genetic search is slow in obtaining solutions and there can be problems determining when a global rather than a local *FDi* has been obtained.

These techniques allow the analyst to overcome weaknesses of one analysis technique by transforming a system model into an equivalent logic model as another analysis technique. For example, a complex system that may be hard to model as a *FTr* might be easily modeled. However, the use of this method shows itself difficult for systems strongly dependent on time. Finally, there is no formal method to verify the exactness of the developed tree. Furthermore, *FTA* can be used to identify multiple faults in a system *FDi* capability. However, the use of this method shows itself difficult for systems strongly dependent on time. Finally, there is no formal method to verify the exactness of the developed tree.

III.6.4.2 - Fault Tree Analysis

FTA *(Vesley et al., 2002)* is widely used in industry for safety analysis. *FTA* is a top-down symbolic logic model generated in the failure domain. This model traces the failure pathways from a predetermined, undesirable condition or event, called the *Top* event, of a system to the failures or faults (*FTr* initiators) that could act as causal agents. Previous identification of the undesirable event also includes recognition of its severity. An *FTA* can be carried out either quantitatively or subjectively.

The *FTA* includes generating a *FTr* (symbolic logic model), entering failure probabilities for each *FTr* initiator, propagating failure probabilities to determining the *Top* event failure probability, and determining cut sets and path sets. A cut set is any group of initiators that will, if they all occur, cause the *Top* event to occur. A minimal cut is a least group of initiators that will, if they all occur, cause the *Top* event to occur. A path set is a group of *FTr* initiators that, if none of them occurs, will guarantee the *Top* event cannot occur. The probability of failure for a given event is defined as the number of failures per number of attempts.

FTA is a structural approach, in which a complex system hazard is broken down in events that may lead to this hazard. Such events may be intermediate events which are further broken down into basic events. *FTr* gates connect the intermediate or basic events, resulting in a tree with the hazard at the root as the top event and the basic events on the leaves. A simple *FTr* *(Güemann et al., 2008)* with basic events (here *failure modes*) fm_i (I =1… 5) and hazard H is shown in *Figure III.26*.

The *FTr* gates which connect basic and intermediate events are most often simply the Boolean *AND* and *OR* gates. More complex variants of gates, *e.g., INHIBIT*, also exist *(Schellhorn, 2002),* but tool support for *FTr*s is most often limited to *Boolean gates*. The informal semantics of the Boolean gates is that for the *AND* gate, all connected events must occur, for the *OR gate*, one of the connected events is enough to trigger the *Top*-level event.

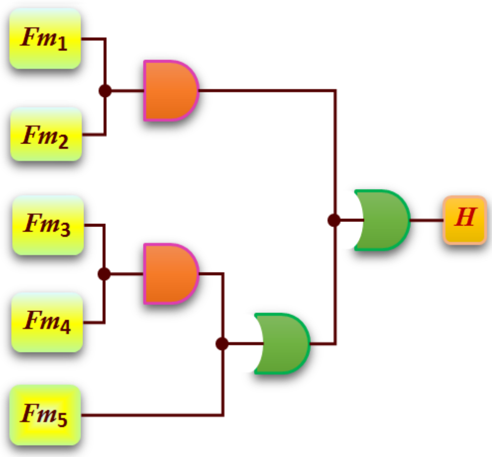


Figure III.26 - Example of FTr.

FTA is used in the aerospace *Pn*, chemical and process pharmaceutical, petrochemical and other high-hazard industries; but is also used in fields as diverse as risk factor identification relating to social service system failure. *FTA* is also used in software engineering for debugging purposes and is closely related to cause-elimination technique used to detect bugs.

FTA's are particularly useful for high energy systems (*i.e.,* potentially high severity events), to ensure that an ensemble of countermeasures adequately suppresses the probability of mishaps. An *FTA* is a powerful *FDi* tool for analysis of complex systems and is used as an aid for design improvement.

This type of analysis is sometimes useful in mishap investigations to determine cause or to rank potential causes. Action items resulting from the investigation may be numerically coded to the *FTr* elements they address, and resources prioritized by the perceived highest probability elements.

FTA's are applicable both to hardware and non-hardware systems and allow probabilistic assessment of system risk as well as prioritization of the effort based upon root cause evaluation. The subjective nature of risk assessment is relegated to the lowest level (root causes of effects) in this study rather than at the top level. Sensitivity studies can be performed allowing assessment of the sensitivity of the *Top* event to basic initiator probabilities.

The procedures, as described in *(Clemens, 1993),* for performing an *FTA* are presented below. These procedures are divided into the four phases: (*a*) *FTr* generation, (*b*) probability determination, (*c*) identifying and assessing cut sets, and (*d*) identifying path sets. The analyst does not have to perform all four phases, but can progress through the phases until the specific analysis objectives are met. *(Kumamoto, Henley, 1996)* provide a detailed description of *FTr* development and analysis for a process system.

In the case of the *KBT*, *FTA* *(Fussell et al., 1974)* was performed using the collected data and heuristic knowledge by industrial representatives and researchers in collaboration. Based on faults, found through interviews, *FTA* *(Andrews, Moss, 2002)* can be performed. In *(Alzghoul et al., 2014),* the *FTA* was used to determine the system elements that need to be monitored. A list of identified measurement points was made and used to detect critical faults through analyzing the *FTA* basic events. Thereafter, the structure and logic of the *FTA* was used to develop the relationships between the measurement points; that is, defining causal relationships between various parameters and parameter sets. *(Hurdle et al., 2005)* presented a method for diagnosing faults or combinations of faults in systems using *FTA* to explain the deviations from normal operation observed in sensor outputs. In this application the logic diagram is used to develop causes of a system symptom exhibited by a sensor reading, in terms of component conditions. The concepts of this method are illustrated by applying the technique to a simplified water tank level control system.

FTA provides the following advantages (*a*) Enables assessment of probabilities of combined faults/failures within a complex system. (*b*) Single-point and common cause failures can be identified and assessed. (*c*) System vulnerability and low-payoff countermeasures are identified, thereby guiding deployment of resources for improved control of risk. (*d*) This tool can be used to reconfigure a system to reduce vulnerability. (*e*) Path sets can be used in trade studies to compare reduced failure probabilities with increases in cost to implement countermeasures.

FTA possesses the following limitations: (1) Address only one undesirable condition or event that must be foreseen by the analyst. Thus, several or many *FTA*'s may be needed for a particular system. (2) *FTr*s used for probabilistic assessment of large systems may not fit or run on conventional PC-based software. (3) The generation of an accurate probabilistic assessment may require significant time and resources. Caution must be taken not to "over work" determining probabilities or evaluating the system, *i.e.*, limit the size of the tree. (4) A *FTr* is not accurate unless all significant contributors of faults or failures are anticipated. (5) Events or conditions under the same logic gate must be independent of each other. (6) A *FTr* is flawed if common causes have not been identified. (7) Events or conditions at any level of the tree must be independent and immediate contributors to the next level event or condition. (8) The failure rate of each initiator must be constant and predictable. Specific (non-comparative) estimates of failure probabilities are typically difficult to find, to achieve agreement on, and to successfully use to drive conclusions. Comparative analyses are typically as valuable with better receptions from the program and design teams.

III.6.4.3 - Decision Tree

DT is popular *inference algorithm* and is one of the most significant techniques in data-mining, initially introduced by *Morgan* and *Sunkist* in 1963. *DTs* are *statistical models* and widely used tools for *supervised training* for *classification,* prediction and *data decisions* *(Michie, Spiegelhalter, 1994)*.

DTs are symbolic learning algorithms based on the knowledge. A *DT* is the main technique that defines the various logical paths that knowledge base must follow to reach conclusions. From the *DT* the relevant rules to each node can be written and so the initial knowledge base can be constructed. A *DT* is a tree structure

consisting of nodes connected by internal and external branches. An *internal node* is a processing unit that takes the *decision* from the assessment of a decision function to determine which *child node* must be visited later. Unlike an internal node, an *external node*, also known as a *leaf* or *terminal node*, *has no children* and is associated with a caption or a value that characterizes the data in that path *(Costa, 2006).* The *DT* plays the role in knowledge discovery while the *FTr* could not.
DTs can contribute to ease and simplicity of developing high-precision fuzzy interference system since *DT* are structurally simple and they could develop *fuzzy rules* and threshold values of membership functions.

In the literature, there are *several methods* and variety of algorithms for the construction of *DTs* that offer the desired quality of interpretation. *DTs* were extensively studied and developed in the 1980s, notably thanks to *Breiman's* work, giving the *CART* model *(Breiman, et al., 1984)* and Quinlan's, giving the *Id*3 *model (Quinlan, 1986)* then *C*4.5 or *J*48 *(Quinlan, 1993)*. The first two methods are well-known *symbolic learning algorithms* that work with *recursive partitioning*. The *basic idea* of these algorithms is to divide the spaces of sampling and to represent the partitions as a tree (a "*divide-and-conquer*" strategy). *(Golmoradi, 2017)* proposed a *fuzzy inference system (FIS)* for monitoring the status of the compressor based on *Daubechies WT* and *DT*s.

What makes *DTs* attractive is the fact that they can represented as rules. The rules can easily be expressed in an interpretable way. *DTs* have been *applied in various areas*, and such *rules* as "if-then" statements can be extracted, which are *easily understood*.

III.6.4.4 - Failure Modes and Effects Analysis

FMEA is widely used for safety analysis in industrial practice *(McDermott et al., 1996; McDermott et al., 2008)* and was used for the first time, from the 1960s, in the field of aeronautics for the analysis of aircraft safety *(Recht, 1966).* This method allows a systematic and very comprehensive component-by-component analysis of all possible failure modes and specifies their effects on the overall system *(Villemeur, 1988)*.

FMEA is a structured, qualitative analysis of a system, subsystem or function that can be used to identify potential system failure modes, their causes and the effects on the system operation associated with the failure modes occurrence. The use of *FMEA* tables for industrial *FDi* purposes leads to the use of a deductive procedure, *i.e.*, to use these tables as a tool for identifying causes of failure from observed effects *(Zwingelstein, 1995).* The modeling of the *CE* relationships carried out by the *FMEA* makes this approach very powerful for the resolution of the problems of *FDi* of industrial process. *FMEA* basically consists of three steps: *FId* modes, determination of the causes for the failure modes and the number of times they occur and definition of detection methods for the failure modes. *(Price, 1999)* demonstrated the use of automated *FMEA* to generate reports that could be used in a *FDi* tool to diagnose multiple faults in systems at one point in time. The failures from the *FMEA* are only generated to a chosen likelihood of occurrence; therefore, all possible outcomes of failure for a system scenario may not be obtained.

The *FMEA* is therefore very widespread in many industrial fields, aeronautics in particular; yet it is heavy and insufficient. Indeed, it is necessary to identify a priori defects and / or malfunctions prior to failures and their possible relationships can never be exhaustive and generally requires a long experience. In addition, any modification or evolution of the system requires a rewriting of the table. Finally, this method cannot handle multiple failure cases and integrate the functional aspect.

III.6.5 - Causality Presentation

Causality tends to be important in qualitative models. Causality is a physical phenomenon based on *CE* relationship between different variables *(Pearl, 2000).* There are *two* basic *kinds* of causal accounts used in qualitative modeling, *structural* and *dynamical*. The causality is used to describe relationships that are algebraic in form. For example, in one part of a causal explanation of the effects of a change on an analog electronic circuit, an increase in voltage across a resistor might cause the current through it to increase. Another example; the increase in heat causes an increase in temperature, which in turn causes an increase in pressure.

III.6.5.1 - Cause-Effect Analysis, Root Cause Analysis

CE reasoning was originally introduced as a reasoning tool to account for the propagation of fault symptoms within a system *(Davis, 1983).* It has been extended to *model-quantitative-based FDI* when *MM*s are available *(Montain, Gentil, 2000).*

A *CE* (or *cause-consequence*) *analysis* is a symbolic logic technique explores system response to an initiating "challenge" and enables assessment of the probabilities of unfavorable outcomes at each of a number of mutually exclusive loss levels. The analyst starts with an initiating event and performs a forward (bottom-up) analysis using an event tree. This technique provides data similar to that available with an event tree; however, it affords two advantages over the event tree - time sequencing of events is better portrayed, and discrete, staged levels of outcome are analyzed.

The cause portion of this technique is a system challenge that may represent either a desired or undesired event or condition. The cause may be a *FTr Top* event and is normally, but not always, quantified as to probability. The consequence portion of this technique yields a display of potential outcomes representing incremental levels of success or failure. Each increment has an associated level of assumed or calculated probability, based on variations of response available within the system.

The *CE relationship* between the inputs and the outputs of a model has *two connotations (Leyval et al., 1994).* From *physics point of view*, the *CE* relation represents the pathway of the signal propagation. From the *computational point of view*, the *cause effect relation* means that any changes in the model inputs will sufficiently cause some changes in the model outputs and the model outputs will not change without any changes in the model inputs.

Popular among these methods are *fault-trees* and *signed digraphs*. *FTrs (Lapp, Powers, 1977)* use backward chaining until a primary event is found that presents a possible root cause for observed process deviation. *signed digraphs (Iri et al., 1979)* is another representation of the causal information in which the process variables are represented as graph nodes and causal relations by directed arcs.

The *CE analysis* is particularly useful in analyzing command-start/command-stop protective devices, emergency response systems, and engineered safety features. Cause-consequence analyses are useful in evaluating operating procedures, management decision options, and other non-hardware systems. Also, it will evaluate the effect/benefit of sub tiered/redundant design countermeasures for design trades and assessment. This technique may be used in conjunction with an *FTA* to provide a technique sensitivity assessment. This technique may also be used to compliment an *FMEA*.

(Zhang, 2018) developed a two-level *FDi* and *root cause analysis* (*RCA*) scheme for a class of interconnected invertible dynamic systems and aims at detecting and identifying actuator fault and the causes. Outputs of the actuator subsystem are assumed inaccessible and are

reconstructed by measurements of the global system, thus providing a means for monitoring and diagnosing the plant at both local and global level. *(Liu et al., 2005)* proposed a methodology for detecting and identifying process faults of multi-operational manufacturing system. For this subject he developed an integrated approach to develop *CE models* from engineering knowledge and to conduct associated statistical analysis of the measurement data. First, a *CE* diagram and *predicted symptom vectors* (*PSV*) are formulated to recognize the *CE* relationship between process variables and product qualities. Then factor analysis and factor rotating technique are employed to extract the relationships reflected from measurement data. Finally, the potential process *faults* are *identified* by comparing predicted symptoms and extracted symptoms.

CE analyses provide the following advantages: (*a*) The analysis is not limited to a "worst-credible case" consequence for a given failure. Therefore, a less conservative, more realistic assessment is possible. (*b*) Enable assessment of multiple, coexisting system faults and failures. (*c*) End events need not be anticipated. (*d*) The time order of events is examined. (*e*) Probabilities of unfavorable system operating consequences can be determined for a number of discrete, mutually exclusive levels of loss outcome. Therefore, the scale of partial successes and failures is discernible. (*f*) Potential single-point failures or successes, areas of system vulnerability, and low-payoff countermeasures are identified and assessed, thereby guiding deployment of resources for improved control of risk and optimized utilization of limited resources.

CE analyses possess the following limitations: (*a*) Address only one initiating challenge. Thus, multiple analyses may be needed for a particular system. (*b*) The initiating challenge is not disclosed by the analysis, but must be foreseen by the analyst. (*c*) Operating pathways must be foreseen by the analysts. (*d*) The establishment of probabilities is often difficult and controversial. (*e*) Determining the severity on consequences may be subjective and difficult for the analyst to defend.

III.6.5.2 - Causal Graph

CG shows relations between variables. It represents a group of influences between variables with a set of relations among themselves. A model *CG* consists of individual nodes connected by quantitative models. The individual nodes represent plant parameters, state variables and measurement variables. The quantitative models represent the *CE* relationship between the nodes.

CGs can be developed with the use of expert knowledge or from equations describing processes, when they are known. There has been a lot of work on automatic methods of building *CG*s using piping and instrumentation diagrams *(Thambirajah et al., 2009)* or archival industrial databases *(Yang et al., 2012)* introduced to express the cause effect relationships. The model *CG* is not a simple network of structural models. It includes the dynamic information about process flow-path, signal flow-path, and control logic so that a fault can be localized based on the cause effect analysis for a process system.
When the directed graph nodes represent the system variables, the directed arcs symbolize the normal relations among them and these relations are deterministic, the graph is frequently referred to as an influence graph *(Gentil et al., 2004)*.

Several major types (categories) of symptoms, which are included in the developed *CG* -modeling structure could be selected, determined and applied in the analysis of the causal relations. (*a*) *Failure symptoms* (or just failures). These symptoms indicate an abnormal behavior of the diagnosed system(s). If a certain failure is detected and/or observed, then the *FD* process can be started. (*b*) *Basic symptoms* (referred also as initial cause symptoms). A *basic symptom* represents a symptom, which is included in the core of the modeling structure, could emerge without any visible reason, and for which there is no necessity to search for any further cause for its generation. This is the most presentable set of symptoms that is determined by the genetic operators (in fact, they create the so-called "pool of the chosen symptoms"). (*c*) *Ambiguity symptoms* are neither faults, neither have they belonged to some of the sub-sets of basic symptoms.
Extended model *CGs* are *multi-model CG*, *model CG with hidden nodes*, *model CG approach with fuzzy inference modeling*, *procedures of model CG approach* and *graph of a process* (*GP*).

A *CG*, which represents a process at a high level of abstraction, is appropriate for supervising the process. *CGs* are useful tools for *FDi* system analysis. This topic was first concerned in *(Iri et al., 1979).* Graph vertices can represent process variables, system components and events like faults and operator interventions. Simulation of fault propagation can be obtained and set of rules for fault discrimination can be built *(Tarifa, Scenna, 1997).* Another application of *CG*s is multiple *FDi (Fang, Pattipati, 2003).*

(Dimitrov, 2009) presented a *CG* approach to *FDi* of industrial liquid waste-processing systems, under real operational conditions. The main goal consists in a development of necessary algorithmic structures, which are applied in an intelligent *FDi* system, based on a deep representation of the knowledge. The *FDi* process is developed as a multi-stage algorithm, consisting of *FDe*, search for solutions, model tests, causal relations among symptoms and faults, and validation procedures.

In *(Sztyber, 2015) GP* is introduced as a new formalization of *CG* useful in *FDi*. The author proposed a method for the generation of model structures (*MSs*) for *FDe* and diagnosability analysis for processes processes where no *MM* is known. The approach is explained on a three-tank system example. The author showed that GP can be constructed on the basis of process diagrams and expert knowledge.

CG is a model which captures deep-level knowledge about process topology. At the same time, the model is very simple and can be easily understood by process engineers. This model can be developed from mathematical description, archival industrial databases, piping and instrumentation diagrams, or expert knowledge. *GP* is a model for clear description of *FDi* knowledge, redundancy searching, and diagnosability analysis. *GP* is not limited to a steady state. Models used for *FDe* should describe process dynamics. *GP* can also describe *NL* processes and transport delays.

III.6.5.3 - Bond Graphs

Among the *graphical approaches*, the *BG (Dauphin-Tanguy et al., 2011)* language allows to deal with the enormous amount of equations describing the process behavior and to display explicitly the power exchange between the process components starting from the instrumentation architecture. It is a unified language for all engineering science domains that considers energy and information channels. Indeed, that is very useful since multidisciplinary systems constitute the majority of industrial products that exist nowadays.

BG is a unified graphical description that presents a domain independent and energy-based methodology for modeling the dynamic behavior of physical systems from different domains (electrical, mechanical, hydraulic, thermodynamic, *etc.*). The causality is an important characteristic used in *BG* models to derive the constitutive equations of the process behavior in a systematic and an algorithmic way. The verification of the causality assignment avoids design and numerical simulation problems.
The *BG* methodology encompasses various kinds of information due to its *causal* and *structural features* that enable to *deduce* directly a set of fault indicators.

BG has been used *to generate residuals* in a systematic and generic way. Recently, the *BG model* the parameters uncertainties in order to generate robust and adaptive thresholds for the residual's evaluation stage. The procedure for obtaining *residuals* is based on covering causal paths *(Samantaray, Bouamama, 2008)* and is implemented in dedicated software *(Chatti et al., 2013; Xiaotian, Anlin, 2014).* Notice that *(Djeziri et al., 2007)* proposed *BG modeling approach* in the *LFT* (*Linear Fractional Transformation*) configuration that enables to take into account parameter uncertainties. However, this approach cannot address the measurements uncertainties. *BG* modeling has been used for both qualitative and quantitative *FDe* and isolation *(Feenstra et al., 2001; Ould Bouamama et al., 2005).* The *FDi* procedure using *BG* is given by *(Mosterman, Biswas, 1997). (Fliss, Tagina, 2010)* has presented *multiple FIso* method based on *causal reasoning*. *BG* modeling was used to describe the relationship *CE* existing between process variables, and influence graph method is used for isolating faults. Experimental have shown that the causal reasoning through the example of *influence graph* can *localize multiple faults* in the three-tank process successfully. *(Samantaray et al., 2006)* used *BG* for *FDe* and *isolation*.

The main advantage of *BG*s is their description of process dynamics. On the other hand, the model is rather limited to linear differential equations. The main drawback of the *BG* approach is a need for detailed mathematical description and estimations of model parameters. Also, in some cases fault influence modeling is needed. Another issue is model complication. Though *BG*s are widely used for modeling, they are not well understood by process engineers. To work with experts, we need easier process descriptions.

III.6.5.4 - Directed Graphs

Directed graph is used to describe causal relationships between process variables and faults. *SDG* is the group of qualitative graphical models to describe process variables and their *CE* relationships in continuous systems, where the process variables are represented as nodes and their relationships through directed arcs. The *SDG* obtained from flow diagrams, *MM*s and empirical knowledge is an expression of high knowledge. The search for patterns in the propagation of faults in a directed graph helps greatly and finds the root causes *(Yang, Xiao, 2005; Yang et al., 2010a).* The hierarchical description of large-scale complex systems is based on the decomposition and approximate aggregation, where a simple *SDG* level model can be transformed into a hierarchical model which makes it easier in the understanding of a complex system *(Celse et al., 2005; Preisig, 2009).*
Graph modeling real system can be obtained from mathematical description *(Maurya et al., 2007),* piping and instrumentation diagrams *(Fan et al., 2010)* and from archival industrial databases *(Bauer et al., 2007; Bauer, Thornhill, 2008).*

Directed graphs can be used to fault symptoms propagation analysis *(Iri et al., 1979; Thoma, Ould Bouamama, 2000)* and to find fault signatures *(Pulido, Gonzalez, 2004; Krysander et al., 2008).* The advantage of using a *DBN* is that it enables comprehensive *FDD* using a single tool as well as it can identify the fault propagation pathway.
(Mallak et al., 2018) proposed a *direct graph-based* approach for sensor or actuator *FDD* of *demand-controlled ventilation* (*DCV*) system. It combines precise and detailed rules represented by the rule-based approaches, and the dynamic solutions, scalability and adaptability offered by the *DDT*s. This approach shows the connection between the *FDi* features extracted from the inserted instances in the ontology and their data properties.

III.6.5.5 - Bayesian Networks

A *BN* is a causal network which belongs to the family of probabilistic graphical models *(Pearl, 1988)* which shows the complex interaction among the variables of a system in the pictorial view. It represents the knowledge in the graphical form. It is a directed acyclic graph, which links up the uncertain observations and helps to reach a certain conclusion *(Neapolitan, 2004).*
The semantic of the *BN* makes it possible to understand the causal mechanism linking a symptom to its root cause. *BN* nonetheless requires more resources compared to the other methods. To set up a Bayesian model, two elements have to be defined: the structure of the network (nodes and arcs) and the network parameters (conditional probabilities distributions).
Although the aforementioned knowledge-based tools can diagnose the root cause of the faults, uncertainty affects their performance. Since process measurements are extremely noisy and *FDi* is a process of reaching to

a certain conclusion compiling several noisy uncertain evidences, the *FDi* tool needs to have robustness to uncertainty. *BN* formalism explicitly incorporates uncertainties and allows exploiting both data and expert knowledge. It is widely used in the fields of medical science *(Friedman et al., 2000)*, safety, risk and reliability engineering *(Abimbola et al., 2015; Musharraf et al., 2013)*, dependability and maintenance engineering *(Weber et al., 2012)*. The power of *BN* has not been fully exploited in the area of process *FDD*.
The most robust feature of a *BN* is that it can be constructed with limited data or even in absence of data integrating expert knowledge *(Heckerman et al., 1995; Martin et al., 2012)*.

The conventional *BN*s used in most of the current literatures are discrete and static. *Static BN* cannot model dynamic systems and therefore, it is not suitable for monitoring the dynamic processes, since it cannot capture the temporal relationships among the process variables. *(Yu, Rashid, 2013)* introduced a *dynamic BN* (*DBN*) based process monitoring technique. It is an extension of a static *BN*. It can represent the temporal relationships *(Mihajlovic, Petkovic, 2001)*. A *DBN* has two robust features: *smoothing* and *prediction inferences*. Prediction is forecasting the future of a state in a node based on the current evidence, while smoothing refers to the estimation of the probability of a node in the past based on collected evidence up to current time slice.

BN has been used for *FDi* and applied for various range of systems. It becomes popular due to its ability to incorporate process data with expert opinion, and it has many successful applications in root cause diagnosis. However, it is possible to build a *BN* using expert opinion only when process data are unavailable. Furthermore, it has ample application in the fields of risk analysis, dependability, and maintainability *(Weber et al., 2012)*. An application of a *BN* in dimensionality reduction is available in literature *(Gonzalez et al., 2015*.

(Mehranbod et al., 2003; Mehranbod et al., 2005) used *BN* in sensor *FDiso* in both steady and transient operating conditions. *(Mehranbod et al., 2003)* proposed a *BN* based *FDId* method for three types of sensor faults: noise, bias and drift in steady operating condition. *(Mehranbod et al., 2005)* extended the methodology for transient operating condition. *(Dey, Stori, 2005)* utilized a *BN* to diagnose the root cause of variation of a machine tool. One of the interesting applications of a *BN* was presented by *(Gonzalez et al., 2015*. They used the *BN* for *FDi* as well as dimensionality reduction. Knowledge of a fault was utilized to reduce the network size. *(Atoui et al., 2016)* proposed another *Condensed Semi Naïve Bayesian Network* (*CSNBN*) based *FDi* approach. They collected the structured residuals in an incident matrix which provided the evidence to the *BN* to diagnose the root cause. *(Yu, Rashid, 2013)* used a *dynamic BN* (*DBN*) based process monitoring approach for detecting the fault, diagnosing the root cause of the fault, and identifying the fault propagation pathway.
(Yu et al., 2015) developed a *modified ICA* (*MICA*) and BN based framework which can capture the *non-Gaussian* feature of process data. They showed that a *BN* can be used to diagnose the faults that originated from an unmonitored variable. *(Wang et al., 2017)* used a semi-parametric *PCA* and *BN* based methodology. Semi-parametric *PCA* enables capturing the *NL*, non-Gaussian and non-monotonic natures of the process data. They also demonstrated the capacity of a *BN* to diagnose the unmonitored root cause variable. *(Gharahbagheri et al., 2017)* presented a hybrid framework combining *KPCA* and *BN*. *KPCA* can handle *NL* process data using the kernel mapping function. Limited *FDi* information from *KPCA* was used to update the *BN* and diagnose the root cause of the fault. *(Gharahbagheri et al., 2017)* applied *KPCA* with a *BN* to capture the non-Gaussian feature of process data, and to diagnose the root cause of a fault. *(Mallick, Imtiaz, 2013)* integrated the *BN* with *PCA* to improve its *FDi* capacity. *(Yu et al., 2015)* used *MICA* and the *BN* to diagnose the root cause in an unmonitored variable.

III.6.6 - Advantages and Drawbacks

For large-scale systems, such information may not be available or it may be too costly and time-consuming to obtain. An alternative method for process monitoring is to use *KBT*s. A *KBT* is useful to tackle some limitations such as computational, and modeling requirement; meanwhile it enhances the performance in terms of reducing classification error and increasing robustness due to noise and disturbance, but it cannot eliminate all errors *(Yu et al., 2014).*

Compared with model-based approach, *KBT* is particularly *suitable* for *large industrial plants since* those *NL* real plants are extremely *difficult to model* and *linear approximation* of the model will *introduce* large *errors* in the results. In addition, knowledge-based approach is able to *reduce* the *complexity* of implementing the corresponding safety system and *make* it *flexible* and easy to *understand* and follow. Symptoms are quickly associated with diagnoses. A knowledge-based approach or expert rule practically provides reasonable fault explanation. The strength of *KBTs* is the opportunity to combine *model-based* and *DDTs* in a hybrid *FDD* approach *(Pettersson, 2005), e.g.,* a *DDT* can detect a fault, and a model-based approach can associate the fault to a *FDi*. Combining knowledge-based *FDi* method with real-time process variables monitoring will improve the efficiency and reliability of detecting fault behavior and overall effectiveness of the system. On the other hand, *KBT*s achieved good performance in detecting pre-known faults without the need of a data set as discussed by *(Chiang et al., 2001; Ng et al., 2001; Chih-Min, Yun-Pei, 2008).*

With all the advantages of *rule-based approaches*, they still have some disadvantages that might put many researchers off using them. As the inferred rules are based on the historical failure cases and engineers' experience, it is difficult to search a wide range of yield loss cases beyond the engineers' current knowledge *(Chih-Min, Yun-Pei, 2008).* Furthermore, the enormous amount of effort needed to link the rules and their requirements with the system's components that the rules are applied on. In addition, the continuous need for changing the thresholds within the rules to fit the new system can be considered as another issue. Thus, configuring such systems can take a lot of time and effort *(Bhattacharya et al., 2014*; *Behravan et al., 2017).* Furthermore, while the knowledge-based tools provide excellent performance in *FDi*, they lack in robust detection capacity.

III.7 - Redundancy

In order to improve the reliability and safety considered as key design issues in most computer systems operations such as in aeronautics and *NPs*, *FM* is usually employed to handle online faults by detecting, locating and identifying them in dynamic systems by using the concept of redundancy of *component* (*i.e., sensor, actuator*), *equipment* or *systems*, either *HR, software*, *AR* or *hybrid configuration*.

In wide sense, redundancy is a system property that generally refers to duplication of state information or system function. From a modeling standpoint, *(Mili et al., 2006)* have found the following redundancy categorization: *state*, *functional*, *temporal* and *control*. *Functional redundancy* form arises when, for example, we compute the same function using three different algorithms, and we take a vote on the outputs. We do not distinguish, in functional redundancy, between whether the components that compute the same function are running concurrently, or in sequence. In this thesis, we are interesting of the *functional redundancy.*

Therefore, using *AR* for *FM* is defined as the determination of faults of a system from the comparison of available system measurements with a priori information represented by the system's *model*, through generation of *residual* quantities and their analysis.

As it is shown on *Figure III.27*, there are two types of redundancies. It can be made *physically (i.e., hardware, static (Isermann, 2006), direct (Jin et al., 2009)* or *by model* (*dynamic*) *(Mohammadi et al., 2010; Samy et al., 2011).* For more details on *redundancy* and its *models,* we can refer to *(Willsky, 1976).*

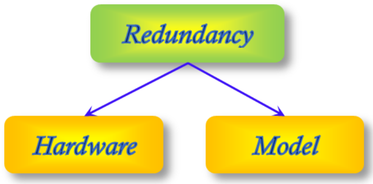


Figure III.27 - Kind of redundancy.

Combination of static and dynamic redundancy lead to hybrid redundancy schemes to avoid the disadvantages of both ones on cost of higher complexity *(Storey, 1996).*

III.7.1 - Hardware Redundancy

In order to improve the reliability of an installation, *HR* called also *simple redundancy (Dorr et al., 1997)* is the first redundancy methods, considered as conventional approach for *FM* and *control (Guo, Musgrave, 1995; Samy et al., 2011; Xin et al., 2015).* The principle of this redundancy is to *duplicate* (double, triple or more), either *identical* or *diverse*, some physical samples of a hardware component in the vast application context. It implements multiple parallel or *hardware* in their *components (e.g., sensor, actuation*, *processors*, *memories), devices* (*e.g., pump),* and *systems* (*e.g., control systems*) *(Napolitano et al., 2000; Goupil, 2011)* in order to measure and/ or control a particular variable of interest *(Hussain et al., 2013; Mouzakitis, 2013).* Outputs from the redundant sensors can serve as references for cross-checking each other and to make consistency checks between related measurements *(Li et al., 2006).*
If these identical components placed in the same environment provide identical signals, one considers that these components are in nominal operation and, in the opposite case, one considers that a fault is happened in at least one component *(Zhang, 1999).* On the other hand, an odd number, usually three, is required if one wants to make the system able to decide (majority arbitration).

There exist mainly two basic approaches for *HR*, *static* and *dynamic*. The *static HR* approaches have been widely used in safety-critical systems for their simplicity and robustness. Their general idea is to measure one critical variable using two or more identical parallel hardware modules (*e.g.,* sensors) that have the same input signal and are all actives as shown by *Figures III.28a* and *b*. Their outputs are connected to a voter who compares these signals and decides by consistency checking and majority voting which signal is the correct one then detects as well as isolate the faulty sensor. If a triple modular-redundant system is applied, and the fault in one of modules generates a wrong output, this faulty module is masked (*i.e.* not taken into account) by the two-out-of-three voting. Hence, a single faulty is tolerated without any effort for specific *FDe*, *n* odd redundant modules can tolerate (n-1) /2. To improve the fault tolerance also the voter can be made redundant *(Storey, 1996).*

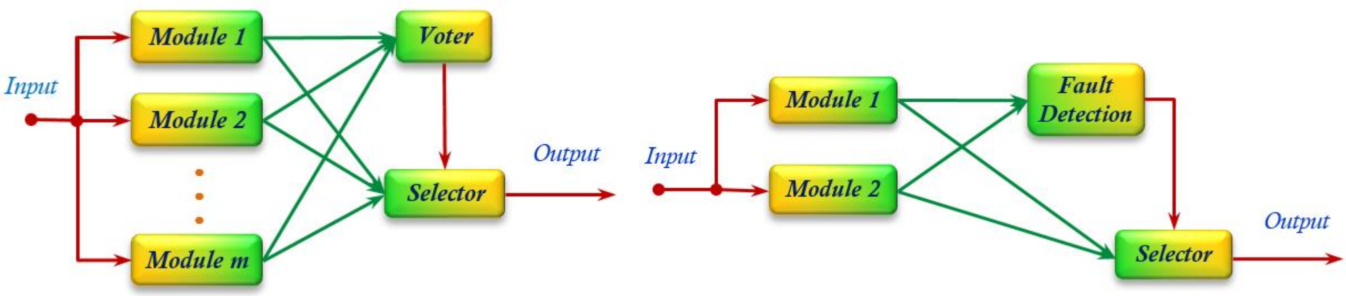


Figure III.28 – Sort of HR: (a: left) static, (b: right) dynamic (Hussain et al., 2015).

Voting techniques are often used in systems incorporating a high degree of parallel *HR*. Voting techniques are fairly easy to implement and mostly suited for *FDi* in instruments with mechanical faults. To describe how a

voting technique will work, consider three identical sensors measuring the same variable. If one of the three signals differ distinctly from the other two, the differing signal is identified as faulty. The difference between the two signals in every pair of sensors in a redundant group indicates a fault.
Typically, a *voting scheme* *(Samy et al., 2010)* is applied to the outputs of the *hardware redundant system* who compares these output signals and decides by majority which signal value is the correct one to *decide* whether a fault has occurred or not and identify any faulty component *(Li et al., 2006; Samy et al., 2011)*.
HR is also used in the cross-calibration *technique* *(Hashemian, 2006),* where the *average* of a set of redundant sensors is considered to be the *true value* of a variable being measured. A fault in a sensor can be detected if the sensor shows any abnormal deviation from the average.
Disadvantages of static redundancy are high costs, more power consumption and weight. Further, it cannot tolerate common-mode faults, which appear in all modules because of common faults sources.
Dynamic HR needs less modules at the cost of more information processing. A minimal configuration consists of two modules as shown by *Figure III.28b*. One module is usually in operation and, if it fails, the standby or back-up unit takes over. The standby module can be continuously active (hot standby) or inactive (cold standby). This requires *FDe* to observe if the operation modules become faulty which is based on generating *residuals* by comparison of measurements provided by *HR* *(Dorr et al., 1997).* A fault in the process component is then detected if the output of the process component is different from that of the redundant hardware. After a fault is detected, the fault indicator (*i.e.,* residual) is used to switch to the standby module and remove the faulty one.

Combination of *static* and *dynamic redundancy* lead to *hybrid redundant schemes* to avoid the disadvantages of both ones on cost of higher complexity *(Storey, 1996).*
Fault-tolerance (*FTo*) can also be designed for purely mechanical and electrical systems. Static redundancy is very often used in all kind of homogeneous and inhomogeneous material (*e.g.*, metals and fibers) and in special mechanical constructions like lattice-structures, pokes-wheels, dual tires or in electrical components with multiple wiring, multiple coil windings, multiple bushes for *DC* motors and multiple contacts for potentiometers. Fault tolerance by redundant kinematics was proposed by *(Tosunoglu, 1995).*

Similar redundant schemes as for electronic hardware exist for software *FTo, i.e.* tolerance against mistakes in coding or errors of calculation. Dynamic redundancy by using standby software with diverse programs can be realizes by using recovering blocks. This means that in addition to the main software module (*e.g., computers*), other diverse software modules exist *(Storey, 1996).*
This same principle is also used for control systems, both for the hardware part (calculator) and for the software part (program). In this case, in order to overcome the program faults (bug), a code developed by three different editors are located on each computer. This is called software redundancy *(Olivier-Maget, 2007).*

Traditionally, *FDIA* is achieved through high-levels of *HR*. This *HR* method has the advantage to be conceptually simple. The main advantage of this scheme is its high reliability and its direct *FIso*. This stills today the state-of-the-art practice in high-performance systems and high-level of operating *security* such as the *aircraft manufacturing industry* *(Zhang, Jiang, 2008; Goupil, 2011)* and *NPPs*. Therefore, *HR* is well known as *high reliability*. This kind of method is very *reliable* and *widely used* in many practical industries *(Li et al., 2006).* So, *HR* is considered critical for the operation of the system and is very wide-spread in the domains where the security of operation is crucial for the safety of the individuals and the environment, such as in the *aircraft manufacturing industry* (*aeronautics*) *flight* control systems *(Samy et al., 2010)* and *NPs.* So, *HR* is used in several works *(Dorr et al., 1997).* Example *(Hussain et al., 2015)* and more details on *HR* are available in *(Napolitano et al., 2000; Zhang, Jiang, 2008)*.

However, by using redundant hardware, the major setbacks and weaknesses encountered are the *extra equipment* which lead to high and serious *cost (economic penalties* and, *installation* and *maintenance cost), power*, *size* and *space,* and *weight implications* and *penalties*. Thus, particularly when the space is very limited in the system, such a satellite *(Li et al., 2006)* and small aircraft's *(Benammar et al., 2011; Hussain et al., 2013),* the application of this scheme is restricted to only a number of key components and uniquely reserved for cases where continuity of service is mandatory, or for critical subsystems whose failure would lead to a disaster (*NPP*, *aeronautics*, *etc*.). In addition to the previous limitations of *HR*, usually identical components can drift in the same manner (direction) and break down in the same time so it is difficult to detect faulty component in these conditions *(Ma, 2015).* To overcome this constraint, the solution is to use different components which insure the same function. Further, it cannot tolerate common-mode faults, which appear in all modules because of common fault source *(Isermann, 2006).* All these over mentioned *drawbacks* make *HR* an unpopular method for *FM*.

However, when reduced *complexity*, *cost*, and *cumbersome*, *weight* are of concern, *AR* *(Dorr et al., 1997)* is more appealing, practical and common approach for *FDD* *(Jin et al., 2009; Hussain et al., 2013)* of *sensor* and *actuator* in systems *(Löfstrand et al., 2012; Witczak, 2007)* and for *nuclear* industry.

III.7.2 - Model-based Redundancy

Due to the *draw-backs, constraints* and *implications* of *HR* and in view of the conflict between the *reliability* and the *cost* of adding *more hardware*, it may not be feasible to use multiple components (*e.g.,* sensors) for the measurement due to physical limitations or due to the specific operating condition. But it is sensible to attempt to use the dissimilar measured values together to cross check each other. This procedure is sometimes referred to as *DR*, rather than replicating individually each hardware. As a result, most *HR* approaches have been substituted by *MBR*, the most frequent scheme *(Frank, 1990),* to overcome the aforementioned barriers. This approach (*i.e., MBR)* is more appealing, common and practical for *FDe* of *S/Ds* in *NR* systems. Furthermore, the continuous development of the computer science and computational techniques have generalized and become the main potential innovation in terms of software forms on computers applied in automated processes. It allows today application, in the industrial environment, modern methods of the automatic and the *AI*. This new approach allows eliminating partially, even altogether, *HR* for the monitoring of industrial systems *(Benammar et al., 2011). (Dorr et al., 1997)* presented a comparative study of sensor *FDe* methods using *HR* and *AR* which have been applied to a real process.

AR is an interesting tool for monitoring studies. It uses a model to predict the output quantity. The difference between this prediction and the measurement of the output constitutes a *fault indicator*. If this difference reaches a significant value, it becomes a symptom of the abnormal behavior of the system: one of the components or devices of the physical system is faulty *(Olivier-Maget, 2007).*
The *MBR* (*functional, computation strategy*) is the manner of identifying a failed instrument in a system using a *fault- model-free* of the system and comparing its estimated outputs considered as *references* to the measurement of the actual, *i.e.,* real behaviors, of the system able of replacing a faulty sensor *(Napolitano et al., 1995).* These references can describe *normal operation* when it is about the *FDe* or the various *types of fault* when it concerns the *analysis* or the *isolation of faults*. So, *MBR* uses a *model* of the monitored system to estimate continuously the output process signal-based on the actual inputs which requires the processing of various accessible process measures. But the model should not, however, be too complicated, because calculations easily become very time-consuming *(Chen, Patton, 1999).* So, *MBR* for *FDD* used the *model* of system to generate a signal called *residual* from the difference between measured parameters and estimated values (see *Figure III.29*) which becomes large in the case of fault and small in the absence of fault.
Finally, this is the concept of *AR* which uses redundant analytical relationships between various measured variables of the monitored process.

After that, *faults*, *noise* and *disturbance* in terms of *residuals* are *evaluated* and *isolated* by computing suitable thresholds. However, the essential barriers of *FDi* isolated by *MBR FDD* are classification *error*, *modeling* requirement, *novelty identifiability* and *computational* requirements (Yu et al., 2014).

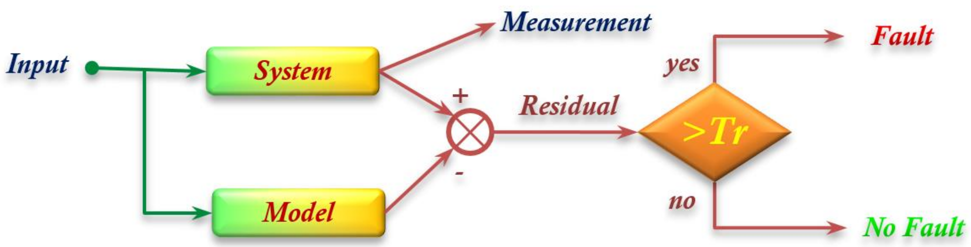


Figure III.29 - Block diagram of AR.

Usually, providing a *FDi* system consists in making a comparison between the measured information, during the actual operation of the system, and the a priori knowledge of its modes of operation. Based on the results obtained from this comparison, the user can intervene and put in place the corrective actions necessary for a return to normal.

AR is obviously a more favorable approach when *weight optimization* is a primary concern (Napolitano et al., 1995). It needs fewer modules at the cost of more information processing. A minimal configuration consists of two modules (Isermann, 2006). *AR* is used for *FDe* of *sensor* and *actuator* as presented in (Witczak, 2007; Löfstrand et al., 2012) and some authors have applied *AR* in the *nuclear industry* (Feeley, 1983).
Typically, a *DDT* such as *PCA* or *FiDiAn* can appropriately and conveniently detect faults in terms of *residual* generation. Although *model-based* approach can provide physical understanding for *residuals*. These *residuals* may include disturbance and noise due to measurement and control signals leading to the degradation of *detection* robustness.

The conceptual *MBT diagram* for a *FDi* system is depicted on *Figure III.30*. It consists essentially of two sequential *steps* (*stages*) namely: (*a*) *residual generation* and *residual evaluation* considered as the key phase of the *FM* in order to determine the state of the process, and (*b*) *residual evaluation* (Palade et al., 2002; Campa et al., 2008).

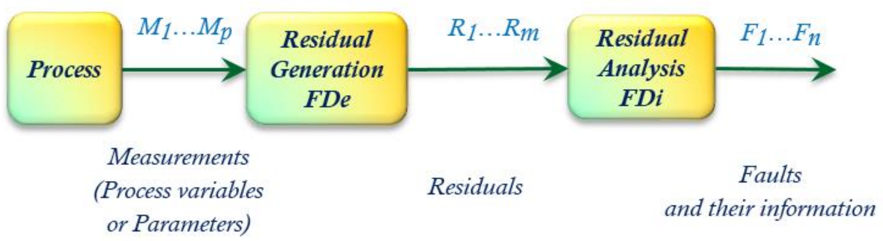


Figure III.30 - The general structure of FDi system (Palade et al., 2002).

Difficulties with model-based *FDe* methods arise from the fact that the *accuracy* of the *measurements* needed to calculate the evolution of faults *should be* of *high quality*. In practice, *FDe* systems make usually use of measurements from process instrumentation that is not necessarily installed for this purpose. In consequence, the *instrumentation* may *not be sensitive* enough and special sensors should be connected to the process equipment. Use of *MBTs* may require assumptions about the process that are not valid, such as the assumption that the process is *linear* as well as that the *influence* of *noise* and *disturbances* to the *FDe* process is of minor importance. Recent contributions to model-based *FDi* include (Korbicz et al., 2004; Isermann, 2005).

III.7.2.1 - Quantitative Methods

A - Analytical (Mathematical) Model-based Redundancy

In parallel of the *HR* *(Jiang, 2011; Zemouri, 2003)* belonging to the *MBTs* *(Olivier-Maget, 2007),* has been recognized as an effective technique for monitoring *(Frank, 1990).* Simulation studies and experimental results have shown that the *FDI* schemes using *AR* have reached a certain degree of maturity. For the sensor failure case, *AR* is often introduced along with, at least, a dual *HR* *(Napolitano et al., 1995).*

Over the past *decades* many *SFDA* publications have targeted fixed *model-based* approaches, with *MM-based* methods being the most popular *(Isermann, 1997)*.

AR methods require a *MM* of the system to monitor. This model includes a number of parameters which the values are assumed to be known during nominal operation. In so far as the monitoring is established from the sampled measurements of the observable quantities of the system, the modeling of this latter in discrete form seems to be reasonable *(Zemouri, 2003).*

AR relationships are used when the model involves measurable quantities. *AR* relationships are relationships between available system variables taken in a time window.

An alternative approach can take advantage of *AR* *(Patton et al., 1989)* to provide *SeV* capabilities. *AR* essentially implies taking advantage of the functional relationship existing between the system inputs, states, and outputs; in other words, *AR* is available when the modeling of the system is known or at least partially known. The comparison with actual state provides residual that will be used to determine if the system is in a failed state or not.

In the literature, several *approaches* are presented, where they base their *AR* on different *mathematical modeling* techniques. Sensor and actuator fault are detected and identified using *AR* as presented in the different works *(Niemann, 2012).* *AR* based methods have been widely discussed by several authors *(Isermann, Ballé, 1997; Blanke et al., 2000).* Specific applications have also been developed in the field of *flight control systems* *(Napolitano et al., 1995)*.

Some authors have applied *AR* in the *nuclear industry* *(Holbert, Upadhyaya, 1990)* *aeronautics* *(Labarrere et al., 1978)* or *chemical industries* *(Swartz, 1989).* Comparisons of the performances of the different approaches of *AR* exist in *(Dorr, 1995)*

B - Data-driven Redundancy

Beside Model, *FDe* is also carried out using *DDT* such as statistical testing methods *(Isermann, 1984).* If precise analytical models are not available or difficult to obtain, like in *NRs*, the model-based *FM* approach is still difficult to apply. In such cases, the support by *DDTs* may be the solution. In these techniques applied to the *FM*, we find the category: *digital* (*e.g.,* delivered by *sensor*) and/or *symbolic* as *knowledge, historic* and/or *instantaneous*, on the considered system. Several studies were presented and various *methods* have been proposed about *FDe* using *data-based* methods in which data can be *quantitative* (*e.g.,* output of sensors), and/or *qualitative* (*e.g.,* observations made by operators) *(Racoceanu, 2003; Srivastava et al., 2014; Simsir et al., 2016).* The *accuracy* of the *DDTs* depends on the applied algorithm; thus, the results may vary from one algorithm to another *(Alzghoul, Lofstrand, 2011).*

The use of *DDTs* includes *statistical methods* and *AI* for *FM* is justified because it is possible to model the process without the need a deep and a specific knowledge about the monitored system (*i.e., algebraic equations*), by using only the *process measured database* *(Mohammadi et al., 2010)* which contains the process *plant information* *(Mandal, 2015).* In addition; *DDTs* have the ability to capture information and provide knowledge which is beyond the engineers' current knowledge *(Chih-Min, Yun-Pei, 2008; Das, Maiti, 2012).* However, *data-driven models* cannot be built without data sets. Therefore, when *ABTs* are difficult to apply, *DDTs* can be considered *(Kourd et al., 2013).*

III.7.2.2 - Qualitative Methods

The idea behind the qualitative observer-based *FDI* is that a fault causes a deviation of the system output in such a way that its counterpart of the estimated output is no more consistent, *i.e.* a fault will produce an empty set of qualitative estimated states, which is impossible in a fault-free case. A model for *FDI* can now be derived following the basic idea of using *fuzzy relational models*.
The *fuzzy observer* is founded on a *fuzzy relational model* of the process, which is formed by the *composition operator* (*T-co-norm/T-norm operator*) applied to a fuzzy *relational matrix* R defining the relation between process input and output, and the fuzzy Cartesian product of the fuzzified input-output signals and its delays on a time window. The fuzzy residual generator as shown in *Figure III.31* determines the difference between the measured and the estimated output using a fuzzy output observer.
Note that the structure of the residual generator based on fuzzy relational models is similar to the one based on neural nets. A basic difference is that the signals used for the fuzzy relational model have been previously fuzzified, for the neural net approach the measured signals are utilized directly.

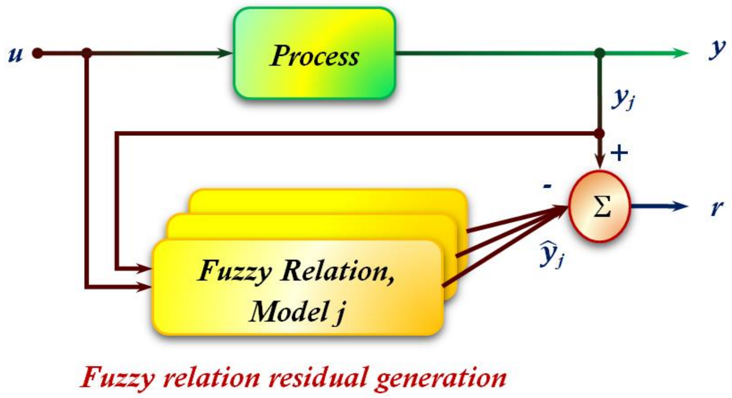


Figure III.31 - Fuzzy observer-based residual generation.

III.7.3 - Residual

(Mehra, Peschon, 1971) introduced a general procedure for *FDI* using *innovations* (or *residuals*) generated by a *KF*. On the other hand, for non-additive failures, even for linear state systems, the known results are less abundant. The situation is even less flourishing for *NL* systems. However, in order to monitor low amplitude failures, a general approach has been developed at *IRISA* *(Zhang, 1999)* which, based on a local approach, allows the design of algorithms for the generation of residuals from the estimation functions and for their evaluation. It applies to a broad class of *NL* systems with additive or none *(Zemouri, 2003).*

The purpose of the residual is to be sensitive to the presence of faults. Thus, normally, in the absence of failures, that is to say in normal operation, the residual must have a value of zero. On the contrary, in the presence of a fault, the residual will have a non-zero value *(Kempowsky, 2004).*

III.7.3.1 - Residual Generation

Figure III.29 illustrates the simplest form of *AR* method and most general principle for residual generation for *FM*. The *error signal*, *prediction error* or *residual* *(Isermann, Ballé, 1997)* is based on signal measure produced by the *difference* (*i.e., comparison*, *discrepancy, changes*) between currently (actually) coming *observed output* (as measurement reading) of the behavior of the operating process (real system) or the *simulation value* of the process variable and the *predicted* (*reconstructed*) *output* of an *exact nominal* (Far, 2007) (*typically empirical*) (Baraldi et al., 2011a) process model estimating the values of *measurable variables* (*signals*) in *normal* (*no faulty*) conditions made by the *model* of the system to be monitored, driven by the same inputs (Samy et al., 2011; Fuente et al., 2012). Therefore, the *residual* signal reflects the *correlation* and *inconsistencies* between the behavior of observed system conditions and the expected ones that should result under normal conditions and its shape represent the fault signature(Calado et al., 2001; Korbicz et al., 2004). Particularly, when the *KF* is used as predictor, this residual is called the *innovation*

So the residual can be formulated as:

$$r(k) = y(k) - \hat{y}(k) \qquad \text{(III.4)}$$

where y(k) and ŷ(k) are the measured and estimated outputs, respectively.

However, in real-life conditions, the filter residuals may be *nonwhite* and/or *biased* due to: (*a*) occurrence of a *sensor failure*; (*b*) bad measurement and/or *intermittent* failure (statistical outliers, data gaps, temporary loss of signals); (*c*) use of a *reduced-order filter*, because of constraints on available computational power.

III.7.3.2 - Residual Evaluation

Once the residuals have been generated as shown by *Figure III.32*, they must be evaluated to determine whether or not a fault has occurred. The basic principle of the anomaly and potential *FDe* is to monitor the residual signal-based on the measurements and the predicted signal comparison. The latest is used as reference system, usually calculated off-line (Napolitano, 1996) by *MBTs* (*AMBTs* or *DDBTs*), is considered as the way to indicate the operation state (*i.e., normal* or *abnormal*) of the process and then to determine the deviations from the expected operating conditions, compare the evolution of the real process, validate the correct operation of the process and reconstruct the measurement (Zhang, 2009; Baraldi et al., 2010).

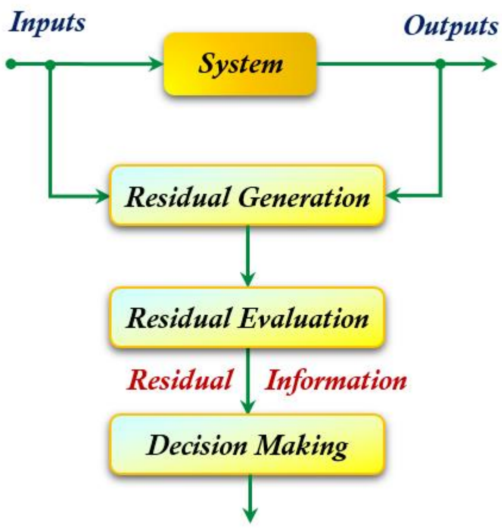


Figure III.32 - Conceptual structure of model-based FDi.

So the *FDe* is performed by using *MBR* approach (Olivier-Maget, 2007), where when *residual* (calculated on-line or off-line) is zero or nearly zero, the system is in normal condition (operation) and regarded as fault-free, conversely when error signals is large and distinctively diverge from zero, the fault is declared (*e.g.,* release of alarm) and the system is defined as in abnormal condition (operation) (Malhotra, Huang, 2002). This zero and non-zero property of the *residual* is used to determine whether or not faults have occurred *(Abdul Rahman, 2010; Fuente et al., 2012).* Therefore, the *residual* is a fault indicator or an accentuating signal which reflects the faulty situation of the monitored system *(Chen, Patton, 1999).* Furthermore when the model is not well designed, small amplitude of the *residual* signal is due to *noise*, *disturbance* and/or *modeling errors (Alzghoul et al., 2014).* However, the residual noise *has* a *mean of zero* and a *variance related to the amount of noise* which helps to its elimination by with *statistical decision logic (Hines et al., 1997a).* The residuals should have favorable properties like minimal sensitivity to disturbances and maximum sensitivity to faults.

As shown by *Figure III.32*, when the *residual* is properly *generated*, in addition to allowing *detection* of faults and the knowledge of the symptom, it helps the *analysis* and *evaluation* of the *residual* by *decision making* to provide a valuable information necessary to describe and characterize the declared faults *(Samy et al., 2011; Fuente et al., 2012).* Then, it allows to validate measured data and *recover* failed *measurements (Chow, Willsky, 1984).*
To *perform* this *analysis* of the generated *signal-residuals*, several *techniques* have been developed, for example, in *(Ding et al., 2004a)* a *statistic method* is presented, in *(Minakawa et al., 1995)* and *ES* is proposed and in *(Garcia, Frank, 1997; Jia-Zhou et al., 2000) NNs* are used. Furthermore, existing theoretical *FDId* techniques (*GLR*, *sequential probability likelihood ratio*, *maximum likelihood detector*, *multiple-model Kalman filtering*) implement a constant *monitoring* of the signals from the sensors of the flight control system *(Napolitano et al., 1995).*
So, in order to detect the occurrence of fault in systems by using a *model-based*, a *dynamic model* of the normal behavior is required *(Blanke et al., 2003).* However, due to the *non-linearity*, *complexity* and absence of *steady-state* operating conditions, the application of the *MMBTs* to batch processes is usually *very difficult*.

Faults in the system are *detected* and *diagnosed* by checking the residual *(Ma, Jiang, 2011).* After that, *faults*, *noise* and *disturbance* in terms of *residuals* are *evaluated* and *isolated* by computing suitable thresholds. However, the essential barriers of *FDi* isolated by *MBR FDD* are classification *error*, *modeling* requirement, *novelty identifiability* and *computational* requirements *(Yu et al., 2014).*
Many techniques are based on the *monitoring* of the *residual signal (Gross, Kumenik, 1991),* for *detecting* a *fault* when the *residual* exceeds a threshold value previously set.
So, any significant *increase* in this *residual* above a specified threshold level (*exceed*) is indicative of *anomalous* behavior, then that system to be monitored is declared as *faulty (Uluyola et al., 2001; Nabeshima et al., 2002).* So, the *residual* is a fault indicator or an accentuating signal which reflects the faulty situation of the monitored system *(Chen, Patton, 1999; Samy et al., 2011).*
The threshold overtaking is therefore used to trigger automatic safety commands such as closing / opening valves if the high limit level is reached, stopping the heating if the temperature has reached the threshold temperature, starting an emergency pump if the usual pump is overheating, *etc. (Olivier-Maget, 2007).*
Thus, the rule of *FDe* is.

$$\begin{matrix} r(k) \leq Th.\ Normal \\ r(k) \leq Th.\ Failure \end{matrix} \tag{III.5}$$

where *Th* is the threshold.
The residual is also used to identify faults *(Samy et al., 2011).* For additive failures in time-constant linear state systems, the generation and evaluation of residuals have been extensively studied, both deterministically and stochastically *(Chen, Patton, 1999).*
A partial list of theoretical *FDI* techniques *(Willsky, 1976; Kerr, 1982)* can be given by: (*a*) *GLR*; (*b*) *Multiple Model Kalman Filtering* (*MMKF); (c) Sequential Probability Likelihood Ratio Test* (*SPLRT*; (*d*) *Generalized Likelihood Test/Maximum Likelihood Detector* (*GLT/MLD*). These techniques *feature* a *CtM* of the measurements from the sensors. At nominal conditions these signals follow some known patterns with a certain degree of uncertainty due to system and measurement noises. However, when sensor failures occur, the observable outputs deviate from the predictable trajectories calculated on-line or off-line from state estimation schemes, namely *KF*s.
The *residuals* evaluation consists to identify all *classes* of system behavior *(Srivastava et al., 2014)* with the goal to diagnose different possible faults *(Köppen-Seliger, Frank, 1995).*

FDI methods are usually based on the residual generation and analysis concept. The residuals should have favorable properties like minimal sensitivity to disturbances and maximum sensitivity to faults. Residual evaluation is making decisions based on these residuals *(Malhotra, Huang, 2002).* The residuals evaluation consists to identify all classes of system behavior with the goal to diagnose different possible faults. When applying the *AR* methods, the evaluation of signal residuals allows to determinate whether component faults, sensor faults or actuator faults are affecting equipment, measuring or control instruments, respectively *(Anzurez-Marin, 2014).* Beside residual evaluation, faults can also be isolated using structured residuals *(Gertler, 1991)*.

III.7.3.3 - Thresholds

Residuals are a crucial issue for *FDe*. During operation, a deviation of the residual values from zero (low value) reveals the presence of an abnormal condition. An ideal residual must remain at zero in the absence of failure and move away from zero in the event of a failure. But in practice, due to the measurement noise, modeling errors and disturbances, a real residual is often different from zero. So, the residual is compared to a threshold instead of zero.

For residual generation, the choice of thresholds is therefore crucial. Therefore, the optimal threshold level must be determined (set) beforehand properly for each system parameters to be monitored, in order to detect accurately abnormality caused by fault.

The threshold is defined by process experts according to safety criteria set by the operator but usually, it is established from a series of simulations in which its value is adjusted, and a trade-off between the *FAl rate* and the *detection capabilities (Napolitano et al., 2000; Olivier-Maget, 2007).* In the opposite case, *FAl* and missed detection may occur, which seriously affects the accuracy of *FDe (Mamar, 2008; Nozari et al., 2011).*
Choosing the threshold at *low-level* would be suitable. However, the presence of *residual* noise (caused by measurement disturbances, process disturbances and model uncertainties) causes the *residuals* to become nonzero which lead to increase the rate of *FAl*s *(Zakrajsek et al., 2005)* choosing it *too large* reduces the net effect of *FDe*. There is therefore a strong motivation to reduce the sensitivity of the *residual* with respect to modeling errors.
If the threshold is chosen too small, *FAl*s occur, if it is chosen large, small faults can be detected. Therefore, it has been shown *(Emami-Naeini et al., 1988)* that it is advantageous to use time-variant thresholds that are adapted to the operation of the system of interest *(Frank, 1996).*
Indeed, a trigger value is too low can frequently generate *FAl*s (related to disturbances). On the contrary, when the trigger value is high, the system is considered in normal operation while it is in default. This fault will then be detected later (especially for the faults settling slowly).
The reason for this is that with *residual* noise being present; thresholds are usually set at a *high-level* to avoid *FAl*s. Consequently, small magnitude faults do not exceed this threshold and pass by undetected. Of course, one can raise the threshold but this can also increase the number of missed faults. A common solution is to amplify the *residual* but this can also have the adverse effect of amplifying *residual* noise.

The choice of optimal threshold of the residual is subject to many difficulties *(Olivier-Maget, 2007)* mainly *spatial uncertainty* and *temporal uncertainty*. The *first one* lies in the choice of the threshold from which the difference between the real value and that obtained by the reference model is considered "abnormal". In this case a threshold that is too low leads to *FAl*s: the situation is supposed to be abnormal when it is not. - On the other hand, a threshold set at a value that is too high risks generating no detection: The situation is assumed to be normal even though it is not. On the other hand, the simulation of the reference model must evolve in real time and synchronously with the monitored process. Usually, this feature cannot be guaranteed at all times. Indeed, a *temporal uncertainty*.) exists because of the intrinsic parameters of the simulation models describing the dynamics of the system. Thus, certain temporal or state events may appear at the level of the simulated reference model either in advance or behind the observations made on the monitored method. Here again, there is the problem of determining from what distance can be considered that a failure is potentially detected. In all cases, a procedure for resetting the reference model to the actual process must be performed in order to be able to validate a detection test.

On the other hand, there are currently several approaches to increase the *FDI robustness* either by a proper *choice* of the *threshold* *(Emami-Naeini et al., 1986)* or by making the *threshold adaptive* to the input, as proposed in the book by *(Patton et al., 1989).* In the simple case, this threshold is *fixed* (a *constant*), but in particular cases, its shape is variable as in the case of *adaptive threshold* to avoid *FAI*s *(Kempowsky, 2004; Olivier-Maget, 2007; Elnokity et al., 2012).*

A - Fixed threshold

The simplest residual test is to punctually compare signals with pre-established thresholds. The *fixed threshold* was the subject of the first work on the problem of choice of the threshold. Crossing this threshold by one of the sensor signals generates an alarm. Practically, there are two types of thresholds. The detection obtained is independent of the time and the type of the system inputs. A *first* type is called the pre-alarm threshold which makes it possible to undertake a preventive maintenance action; the *second* type is the alarm threshold which imposes the stop of the production and the commitment of a corrective maintenance action. This type of method is very simple to implement but seems unsuitable for a system subject to disturbances because it is very sensitive to disturbances and noise, and can lead to *FAI*s as shown on *Figure III.33* *(Zemouri, 2003).* If the threshold chosen is too small, uncertainty cause false signal otherwise small faults cannot be detected.

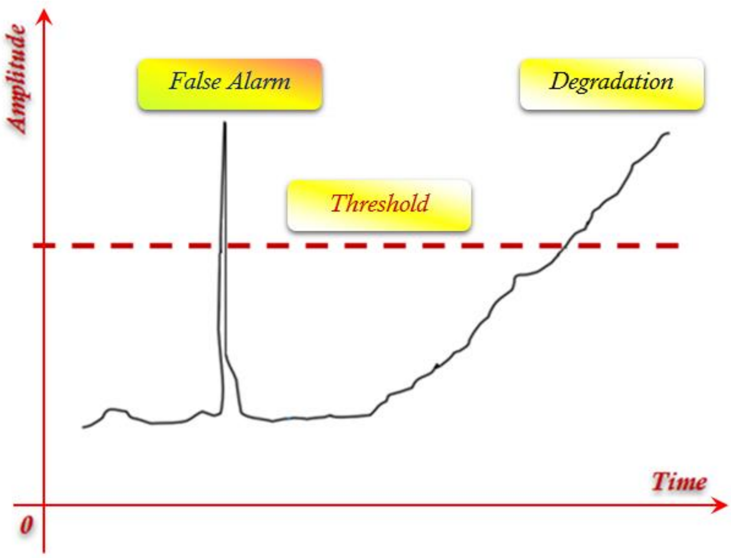


Figure III.33 - Sensitivity of the threshold crossing test method of FAIs.

Using *LC*, the process variables are measured and compared to a known limit for each variable. Typically, the first step is to establish the variables threshold and then to compare them with the measured values. Any measurement or comparison between known threshold and measured value outside the expected range would indicate the presence of fault.

Generally, two limit values of thresholds are preset, a *maximal value* Y_{max} and a *minimal value* Y_{min}. A normal state is when:

$$Y_{max} > Y(k) > Y_{min} \qquad \text{(III.6)}$$

which means that the process is in normal situation if the monitored variable stays within a certain tolerance zone. Exceeding one of the thresholds indicates that a fault is somewhere happen in the process, as shown on *Figure III.34*.

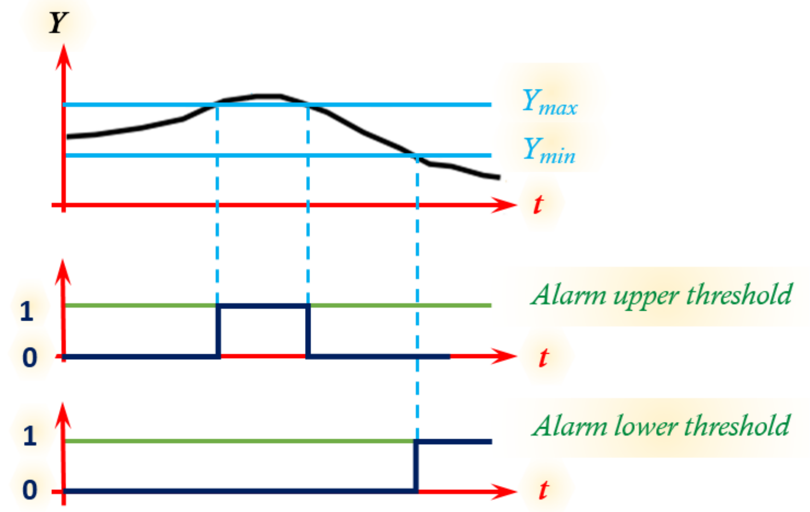


Figure III.34 - Limit checking.

B - Adaptive Threshold

Figure III.35 shows the idea of *adaptive threshold* and it is clear that if a *fixed threshold* is used then the false signal occurs at the time T_{fa} and the fault at T_f cannot be detected. When *adaptive threshold* is used, the *residual* caused by the input in fault-free case, the *FAI* can be avoided and fault at T_f can be detected *(Srivastava et al., 2014).* This figure shows the advantage of using adaptive thresholds rather than fixed thresholds. It can be seen that the adaptive threshold makes it possible to avoid the emission of *FAI*s. Many studies deal with this technique *(Ding, Frank, 1991; Sauter et al., 1996)*.

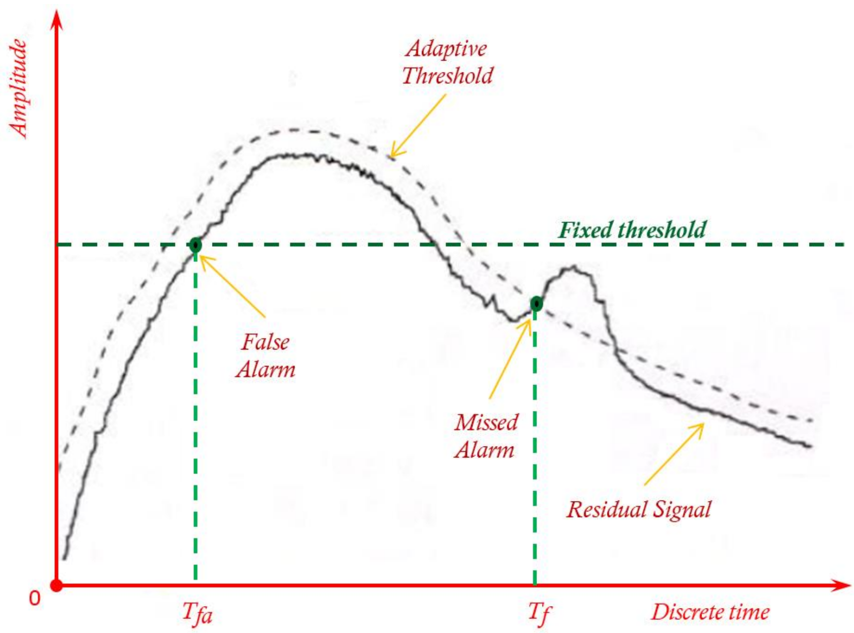


Figure III.35 - Illustration of the concept of the adaptive threshold.

III.7.3.4 - Robustness

Although research on *model-based approaches* for *FM* has been actively carried out with noteworthy results *(Isermann, 2006),* it is still a challenging task, especially in researches related to robustness in presence of different sources of uncertainties *(Keliris et al., 2015), NL* systems and hybrid system issues. Various works focused recently on the design of consistency tests for dynamical systems with additive and multiplicative parameter uncertainties by dealing with intervals analysis *(Puig et al., 2013)*. There exist several *FDI* approaches to handle the robustness issue *(Frank, Ding, 1997)* in which the *model uncertainty effect is suppressed*. The aim of these techniques is not only to suppress all the uncertainty effect but to formulate a mini-max optimization problem in which the model uncertainty is minimized while the sensitivity to the fault is maximized *(Frank et al., 2000a).*

These *robustness* approaches are divided into two groups as *active* and *passive* as shown on *Figure III.36*. The *active robustness* approach deals with the model uncertainty in the residual generation phase. The aim is to avoid model uncertainty effects on the residuals. The *passive robustness* approaches are implemented in the residual evaluation phase, *e.g.*, by using time varying thresholds, also known as *adaptive thresholds*. For further details about robust *FDD*, the papers *(Chen, Patton, 1999; Marcos et al., 2004),* can be seen. A *robust observer FDI* based on *threshold* and *adaptive threshold* methods are applied.

Although *redundancy* techniques are very appealing, there are some important *issues* related to the application of these techniques in terms of *robustness* to *nonlinearities*, *low signal-to-noise ratios* (*SNR's*), and *modeling discrepancies* between the actual system and the filter model. Model-based *FDI* makes use of *MM*s of the supervised system; however, a perfectly accurate and complete *MM* of a process is never available in practice. Usually, the parameters of the system may vary with time in an uncertain manner, and the characteristics of the disturbances and noise are unknown so that they cannot be modeled accurately. Hence, there is always a mismatch between the actual process and its *MM* even if there are no process faults. Hence, there is always a mismatch between the actual process and its *MM* even if there are no process faults.

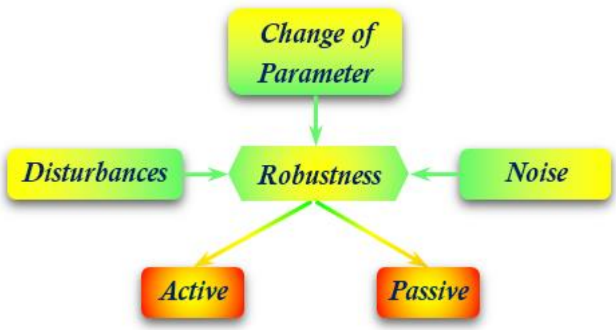


Figure III.36 – Robustness.

Hence there is a need for developing *robust FDe* algorithms (*i.e., reduce* the *sensitivity* of the *residual* with respect to these negative effects. The model must only be sensitive to faults, even in the presence of the perturbation and interference). Ideally a *residual* is nonzero only when a fault is present, so it carries information only about fault *(Fuente et al., 2012; Khireddine, 2014).*

However, in real applications, the residuals may be influenced by the presence of *undesired effects* such as *disturbances*, *interferences*, *noise* and *modeling errors* which represent unknown and uncontrolled inputs acting on the system. Therefore, the *residual* will always be nonzero due to unknown inputs and other *uncertain factors* which represent unknown and uncontrolled inputs acting on the system and consequently, interfere with the detection of faults *(Chen, Patton, 1999; Samy et al., 2008)* which make the *residual* as *stochastic process* *(Xin et al., 2015).*

Thus, for the purpose of *FDiso*, *(Patton, Chen, 1997)* proposed to compute the residuals by decoupling the effect of a fault from the effects of different inputs (the disturbance decoupling principle) and from other faults. This can increase the risk of *FAI*s especially if simple threshold logic is implemented for *residual* evaluation.

The model uncertainties and their effect are the most crucial point in the *model-based FDI* concept have to be considered since they may lead to a bias in the residuals, which can be interpreted as a faulty situation. The solution of this problem is the key for its practical applicability.

To overcome the difficulties introduced by modeling uncertainty, a model- based *FDI* has to be made robust, *i.e.* insensitive or even invariant to modeling uncertainty. Sometimes, a mere reduction of the sensitivity to modeling uncertainty does not solve the problem because such a sensitivity reduction may be associated with a reduction of the sensitivity to faults *(Chen, Patton, 1999).*

Hence there is a lot of effort and strong motivation has been invested to overcome the difficulties introduced by *undesired effects* for developing robust *FDe* procedure (to reduce the sensitivity with respect to negative effects) which means that model has to be a crucial issue and *robust* against the presence these *negative factors* (perturbation and interference) in manner that this model be only sensitive to faults *(Korbicz et al., 2004; Ben Rahmoune et al., 2017).*

After presenting the basic *FDI* approaches, their structures and design parameters, we now focus our attention to solve the central task of residual generator design: making the *FDI* system robust to the model uncertainty and disturbances, and simultaneously sensitive to the faults.

The importance of robustness in model-based *FDI* has been widely recognized by both academia and industry. The development of *robust* model-based *FDI* methods has been a key research topic during the last decades. A number of methods have been proposed to tackle this problem, for example, the *UIO*, Eigen structure assignment, optimally robust *parity relation* methods. However, the research is still under the way to develop the practically applicable methods *(Chen, Patton, 1999).*

The *robustness* problem has been recognized early on and several approaches to increase the *robustness* of *FDI* schemes have been suggested over the years. *Frank* and *co-workers* have developed state estimator design techniques for *robust residual* generation, the results of which are summarized in *(Claek, 1978)* and in the book by *(Patton et al., 1989).* Other significant contributions to the *robust observer* design for *FDI* were made by *(Ge, Fang, 1988; Patton et al., 1989)* and others. In *(Lou et al., 1986)* the robustness problem was primarily tackled from the *parity space* point of view. From this perspective the *residual* of an estimator can be viewed as the most general *parity* function containing the complete set of redundancy relations. The underlying idea of robustness generation is to utilize only those redundancy relations that are most reliable. Procedures for finding optimal solutions are given in *(Lou et al., 1986).*

(Fonda et al., 2010) proposed a method to develop robust observers with respect to noise, unmodeled dynamics, unknown fault dynamics and disturbances, using *NN* based *Online approximation (OLA)* with *RISE* feedback structure. The proposed method increases observer robustness while improving performance over conventional observers utilized for *FDe* unknown fault dynamics and disturbances, using *NN* based *OLA* with RISE feedback structure is proposed. The observer outputs are utilized to perform *FDi*.

Another famous approach is the *UIO* which attempts to decouple the effects of *unknown inputs* *(Watanabe, Himmelblau, 1982)*. Alternatively, *(Samy et al., 2008)* suggest a novel *residual* processing approach which will be referred to as *residual* padding. A model-based *FDI* has to be made *robust* *(Chen, Patton, 1999). (Horak, 1988),* mainly used adaptive threshold for robustness.

Sometimes, a mere reduction of the sensitivity to modeling uncertainty does not solve the problem because such a *sensitivity reduction* may be associated with a reduction of the *sensitivity* to *faults*. A more meaningful formulation of the *robust FDI* problem is to increase the *robustness* to *modeling uncertainty*, whilst

without losing (or even with an increase of) fault sensitivity. An *FDI* scheme designed to provide satisfactory sensitivity to faults, associated with the necessary *robustness* with respect to modeling uncertainty, is called a *robust FDi* scheme *(Patton, Chen, 1997).*
Ways to improve model-based *FDI* robustness to unknown inputs is a widely studied topic. Examples include *adaptive thresholds*, originally proposed in *(Emami-Naeini et al., 1998),* or the application of alternative *residual* evaluation techniques which do not rely on simple threshold logic, *e.g.,* statistical tests on the *KF innovation* sequence.

Robustness can be achieved in the *residual generation* stage known as *active*, or in the *DM* stage known as *passive* mainly using an *adaptive threshold (Chen, Patton, 1999)*. For more details on *passive* and *active approaches* for robust *FDe*, see *(Puig et al., 2007).*

III.8 - Signal Processing

During the past decades the use of *SP* methods in the *fault feature detection* has gained important attention and a large variety of *SiBTs* have been used to detect undesirable performance changes in industrial systems *(Ma, 2015).* These methods are often used to monitor process signals to extract features that can characterize component conditions. Based on these features, health of the equipment can be assessed using engineering judgment.
SP methods consisting of: (*a*) *periodic signals* (*e.g., band-pass filtering*, *Fourier analysis*, *spectral estimation* and *correlation functions);* (*b*) *stochastic signals*; and (*c*) *non-stationary signals* which include *WT* and *short-time Fourier* analysis *(Isermann, 2011).*

Usually, the acquired signal always contains noise and interference that affects the signal characteristics that will mislead the analysis of signal and provide the wrong indication. So, good *SP* tools is required to clean (*i.e.,* reduce the noise) the signal without removing the important features to turn the signal more informative.

SP for *FM* is used when the possibility of building a reliable model and identifying of its parameters are limited. Indeed, *SP* use *measured signals* rather than explicit *input-output models* for *FM*. *SP* can be applied when changes in signal are related to faults in a process. *SiBTs* make *FDe* decisions by comparing desired normal behavior with features (*e.g.,* spectrum) extracted from a signal. By assuming *MMs* for the measured signal, suitable features are calculated (*e.g.,* amplitudes, phases, and spectrum), and are considered as analytical symptoms which give a deeper *insight* into the process behavior. Features in *time domain*, *frequency domain, and joint time-frequency domain* have been used.
A general scheme of the *SP* for the purpose of *FM* is presented in *Figure III.37 (Do, Chong, 2011).*

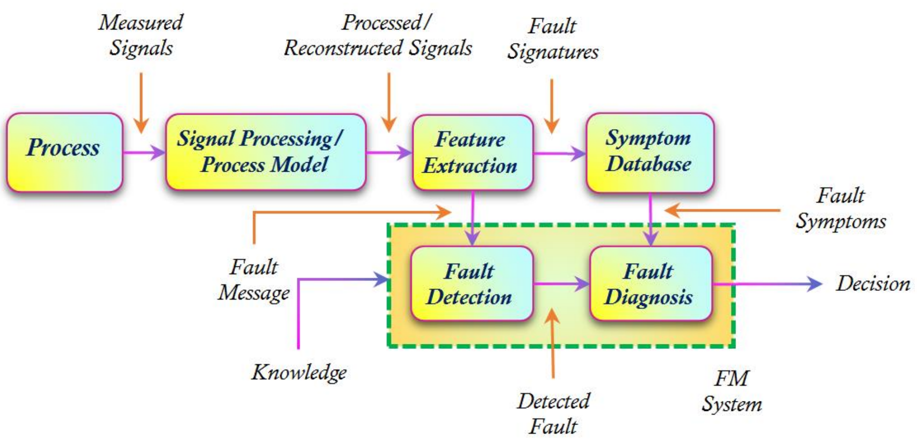


Figure III.37- SP scheme for FM.

On the hypothesis that information about the *faults* in the process are *reflected* or *carried* in some *measured signals*. The *SP* methods analyzes the acquired signals to *extracted features* as *process variables* and to generate the *fault symptoms* or *signatures*, which can be analytical or heuristic symptoms (Isermann, 1997; Ding, 2008). The *signal features* well known are *time domain functions* like *magnitudes*, *arithmetic* or *quadratic mean values*, *limit values*, *trends*, *statistical moments* of the amplitude distribution or envelope, or *frequency domain functions* like *spectral power densities*, *frequency spectral lines*, *spectrum*, *etc*. The *fault symptoms* are the input of the *FDi* process that determines the size, type and location of the system fault. Then, a *FDi decision* is then made based on the symptom analysis and prior knowledge on the symptoms of the healthy systems.

In industries, often parameters to be monitored are the *induced effects* by the system operation. The *SiBT*s consider input and output of the device measurement signals as key characteristics. The most used measured signals are: *mechanical vibration*, *acoustic*, *magnetic*, *thermic*, *IR thermograph* and *electric*. The vibratory signatures, are adapted to the detection of anomalies affecting mechanical assemblies whose structural elements are subjected to dynamic forces resulting in mechanical vibrations. Vibration analysis detects repetitive movements of a surface belonging to a dynamic mechanical material (*rotating machines*, *alternative machines*, *etc*.) or to a *static material* (*structure*, *piping, etc*.). For the majority of the defects found on rotating machines the vibrations are periodic in nature. For defects that result in shocks to structures, the vibrations are characterized by transient signals of short duration, repetitive or random. There are also random signals over time (*e.g.,* cavitation in hydraulic machines).

Acoustic signatures originate from the noise induced by certain phenomena such as leakage of fluids through small openings (sealing problem), cavitation in hydraulic machines, and vaporization due to overheating in steam engines. Acoustic signature is based on listening to noises emitted by the materials when they are put under stress.

The approaches to *FDe* involve various methods and algorithms of *SP* (Dai, Gao, 2013). The *feature signals* to be *extracted* for *symptom* (or *pattern*) *analysis* can be either *time-domain* (*e.g.*, *mean*, *trends*, *standard deviation*, *phases*, *slope*, and *magnitudes* such as *peak* and *root mean square*) or *frequency-domain* (*e.g.*, *spectrum*). Therefore, signal-based *FDi* methods can be thus *classified* into *time-domain*, *frequency-domain* and *time-frequency SiBTs*. The basic groups of methods which employ *SiBT* to *FDe* are presented in *Figure III.38.* It should be emphasized that the *FDe* methods utilizing *SA* of the signals play an important role in analysis of all types of signals: periodic, non-stationary and stochastic ones.

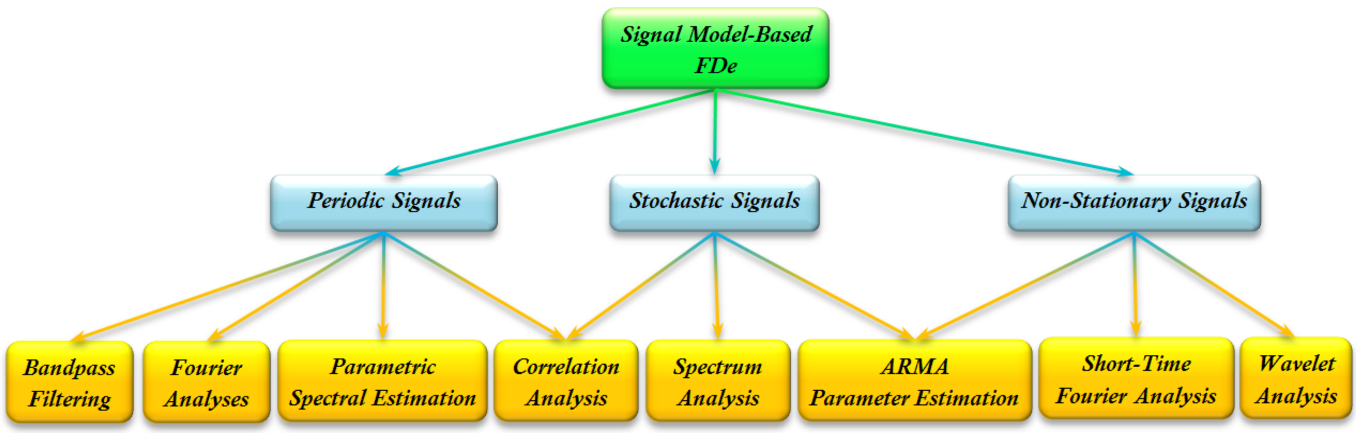


Figure III.38 - FDe methods based on signal models (Świercz, 2015).

III.8.1 - Time Domain

Time domain refers to analysis or display of signal axis with the function of amplitude and time. Every signal contains several *time domains* features that are very informative for *FM* and are usually related to *statistical* *parameters extracted* from a signal such as *peak value, mean value, RMS value, cumulative sum* (Montgomery, 2009), *kurtosis, skewness* and *exponentially weighted moving average* (*EWMA*) (Hunt, 1986). Therefore, for a continuous dynamical process to be monitored, it is natural to *extract time-domain features* for *FDe* and *FDi*.

The statistical methods and time series modeling methods are applied in *FDe* tasks. Several *statistical parameters*, calculated in the *time domain*, are generally used to define *average properties* of process variables, which can change after fault occurrence. The two basic parameters are the *mean* value and the *standard deviation*. These *statistical parameters* may be used to perform a quick check of the *changes* in the *statistical behavior* of a signal.
In addition, under different defect model, the statistical analysis will produce a different statistical feature of time domain data. The *AutoRegressive Moving Average* (*ARMA*) modeling is used commonly in time series analysis, due its simplicity and ability to *show sharp peaks* in the *frequency domain*. The *autoregressive* coefficients of the model represent signal features, which can be used for *FDe* purposes. *Autoregressive* modeling is a *parametric method* which can be used for *signal prediction*, what can be employed to forecast the fault occurrence.

The extraction of fault-relevant signal characteristics can be restricted to the amplitudes or amplitude densities within a certain bandwidth of the signal. Despite their effectiveness, the classical digital *SP* techniques have several *limitations* to be considered *for a reliable FM*. The *main restriction* on practical use of classical techniques on real signals is caused by *additional noises* which are always present in any industrial environments and may result in *erroneous decision-making process* (Kia et al., 2013). Another drawback is that classical methods make *little physical sense in dynamic conditions* such as *fast* and *frequent load variation* and other *time-varying circumstances* (*e.g.*in the case of electrical machines).

The conventional simplest and direct method, referred to as an *absolute value check*, is based on single process variable. It consists in releasing a fault symptom as soon as the maximum value (presumed tolerances) of the output signal is exceeded or its minimum value is fallen below. In this approach the distance from the limits to the physical boundaries is a sort of a tuning parameter, which should be set properly, to avoid the appearance of damage on the one hand and unnecessary alarms on the other. More advanced checking can be also applied on the *trend* (time derivative or *speed*), or even on the *acceleration* of the output signal for symptom generation. Also, a *combination* of *absolute* value and *trend* checking is possible.

Big advantage of *LC* is its simplicity and reliability however, they are able to react after relatively large change of feature (Isermann, 2005, Isermann, 2006). The distribution of normal condition (non-fault) data is not always Gaussian, in such cases *GMM*s can be used (Verron et al., 2010). However, the techniques of *LC* have two *disadvantages*: it is *impossible to predict* the *fault* in advance (since the fault has already occurred when detected) and the methods *do not provide* the *type*, *size* and *location* of faults, what can be possible by applying model-based *FDe* techniques (Venkatasubramanian et al., 2003a). Usually, it is assumed that residuals are the sums of two components: one caused by noise (which is a zero-mean random) and the other by faults (which is deterministic, but unknown). The *disadvantage* of this detection method is that normal *fluctuations* around one of the *thresholds* could cause *FAls*.

Furthermore, a mean value identifies on usual values of a signal. If the current value differs strongly from mean, a faulty measurement can be assumed. We compute the mean value over a sliding window with length *T*. Hence, mean is defined by.

$$E\,\{x(t)\,\} = \bar{x}(t) \; = \frac{1}{T}\sum_{\tau}^{T-1} x(t-\tau) \tag{III.7}$$

The Standard Deviation quantifies the width of a probability distribution and defines the expected deviation of a measurement related to the mean. For parametric distribution functions we can calculate the probability of the current difference from mean. Standard Deviation is defined for a sliding window with length *T* by:

$$s\{x(t)\} = \bar{x}(t) = \sqrt{\frac{1}{T}\sum_{\tau=0}^{T}[x\left(t-\tau\right) - \bar{x}(t)]^2} \tag{III.8}$$

The first deviation reflects the dynamic of the observed system. The value allows to recognize outliers, spikes, *etc*. The deviation can be calculated by:

$$\frac{dx}{dt} = \frac{x(t)-x(t-1)}{\Delta} \tag{III.9}$$

The *Signal-to-Noise-Ratio* (*SNR*) allows to estimate the noise level of a signal. In literature it is often defined as signal power divided by noise power. However, to compute a running *SNR* we apply the following definition:

$$SNR\{x(t)\} = \frac{E\{x(t)\}}{s\{x(t)\}} \tag{III.10}$$

The Correlation-Coefficient describes the similarity of two signals. Therefore, the correlation-coefficient is defined as :

$$r_{xy} = \frac{E\{x(t)-y(t)\}-E\{x(t)\}E\{y(t)\}}{s\{x(t)\}\{x(t)\}} \tag{III.11}$$

Furthermore, the Correlation-Coefficient allows to derive a functional relation between to signals. As the coefficient is in the [-1,1] interval, it can be interpreted as:

- $r_{xy} > 0$: high values in x yield high values in y.
- $r_{xy} < 0$: high values in x yield low values in y.
- $r_{xy} = 0$: x and y are not correlated.
- $r_{xy} = 1$: x, y are linear correlated: $y = ax + b$ with $a>0$;
- $r_{xy} = -1$: x, y are linear correlated: $y = ax + b$ with $a<0$;

For instance, in *(Chen, Lu, 2013),* by analyzing the changes of the measured *root-mean-square current characteristics* between healthy conditions and the situations under single/dual transistor short circuit or open circuit, a *FDi* method was developed for power converters of switched reluctance motors. In *(Freire et al., 2013),* the absolute value of *the derivative of the Park's vector phase angle* was used as a *fault indicator*, which was employed for diagnosing multiple *open-circuit faults* in two converters of *permanent magnet synchronous generators* (*PMSG*) drives for wind turbine applications. By observing the *slope* of the *induction current* over time, a *FDi* method was addressed in *(Shahbazi, Jamshidpour, 2013)* for *open* and *short circuits switch FDi* in non-isolated *DC-DC converters*, and the *Field Programmable Gate Array* (*FPGA*) digital target was then used for real-time experimental implementation. In *(Bouzid, Champenois, 2013),* it was shown that, under balanced supply voltage, the *phase* angle, the *magnitude* of the *negative and zero-sequence currents* can be considered *as reliable indicators* of *stator faults* in the induction motors. In *(Samara et al., 2008),* a statistical method for the detection of sensor *abrupt faults* in aircraft control systems was presented, where the *covariance of the sensing signals* was used for *feature extraction*. Different from the approaches for *FDD* using features of the measured signal in one-dimension domain, a two-dimension *SiBT* was proposed in *(Do, Chong, 2011).*

III.8.2 - Frequency Analysis

The *spectral information* extracted from a signal is usually used as *frequency domain features* Most plant variables exhibit a typical frequency spectrum under *NOCs.* Since *different fault types* generate *different frequency* spectrum distributions, the *monitoring* may be *based* on *frequency features of signals*. Therefore, *frequency analysis* of plan measurements can be successfully used in *FM* of dynamic systems. Any deviation from the normal feature can be interpreted as abnormality.

Frequency domain refers to the function of the signal with respect to frequency instead of time. *Frequency-domain SBT* is to *detect changes* or *faults* by using *spectrum analysis tool* such as *Discrete Fourier Transform* (*DFT*).

Frequency domain contains several analyses such as *SA, power spectrum analysis*, *PSD Analysis* and *envelope analysis*. The *FT* is a well-known technique for electrical signal analysis. *Frequency content* of a signal at certain frequency bands can be found by *FT* which is mainly used in the analysis of *periodical signals*. However, when it is applied to *non-periodical signals*, this transformation does not generate satisfactory results *(Santoso et al., 2000; Latran, Teke, 2015)*. Therefore, other analytical techniques designed for *non-periodic signals* must be used. Furthermore, *FT work well* on *stationary*, therefore*, frequency-domain feature extraction* using the *FT* is *unsuitable* when the underlying signal is *nonstationary*, *i.e.* when the signal does not have the same mean/ variation over the entire time domain space *(Riera-Guasp et al., 2015).*
Fast Fourier transform (FFT) is one of the example methods by transforming time series to frequency spectrum (*SA*). It is an efficient algorithm which can be used to calculate frequency content of a periodic signal. *FFT* based on periodic function, can be expressed as an infinite sum of periodic complex exponential function. *Power spectrum analysis* is an inverse of *FT* where the signal is converted to time domain that represents peaks corresponding to the period of the frequency in the spectrum.
However, an *FFT-based method* is not applicable for non-stationary signal analysis due to various factors that affects the signal characteristics such as environment factor and failure in the machine.
While *PSD* is derived after *FFT* analysis where the highest amplitude (power) at a given frequency can be obtained. *PSD* is useful for *FDi* and hidden periodicity finding. Envelope analysis is also known as high-frequency resonance techniques used to determine the resonance excites by the impacts.
The *Cross Power Spectral Density* (*CPSD*) between the input and the output signals can be also *estimated* and used as the *fault indicator*.
Parametric signal models like *ARMA* can also be used to calculate frequency content of signal *(Isermann, 2006; Isermann, 2005).* But parametric models are very sensitive to small frequency changes.

SA is a useful tool to diagnose machine faults using *signals* such as *vibration, motor current (Benbouzid, 2000; Tavner et al., 2008),* and *acoustic emissions (Kunze, 1999; Lee et al., 2006).* In addition, *SA* of process noise is shown to be a useful tool to detect dynamic performance degradation of sensors *(Demazière, Glöckler, 2004; Hashemian, 2006)* and to *monitor NR internal structures (Glöckler, 2003).* Higher order spectral analyses have also been utilized in *FDD* applications *(Liang et al., 2013).*
Vibration signal analysis is a common method for *CM* for *mechanical equipment* such as gear box, as machine sound indicates a lot about working condition of the machine. In *(Pan et al., 2012),* an *acoustic FDe method* was addressed for gear box on the basis of the improved frequency domain blind de-convolution flow. Recently in *(Feng, Zuo, 2013), Fourier spectrum* and the demodulated spectra of amplitude envelope were employed to detect and locate multiple gear faults in planetary gearboxes.
One of the most powerful *frequency-domain methods* for diagnosing motor faults is *MCSA*, which utilizes the *SA* of the *stator current* to sense rotor faults associated with broken rotor bars and mechanical balance. Without requiring access to the motor, the *MCSA* approach has received much attention, which was well *reviewed* in

(Benbouzid, 2000; Nandi et al., 2005). Recent development of *current based spectrum signature analysis* for *FDi* can be found in *(Gong, Qiao, 2012; Joksimovic et al., 2013).*

Finally, we conclude that in the frequency domain, the *frequency resolution* and the *spectrum leakage* are two *important factors* which influence the performance of *frequency domain analysis*. The fault related frequency components in electrical signatures are commonly dependent on time-varying circumstances. An effective solution for minimizing the spectrum leakage is the usage of a convenient window function for data processing *(Al-Dahidi et al., 2014).* The frequency resolution is also a crucial factor since any accurate frequency tracking in a spectrum is essential for a consistent *FDi*. The *FT* is a well-known technique for electrical signal analysis, mainly used in the analysis of *periodical signals*. However, when it is applied to *non-periodical signals*, this transformation does not generate satisfactory results *(Santoso et al., 2000; Latran, Teke, 2015).*

III.8.3 - Time-Frequency

The main challenge for *frequency* and *time-domain methods* is the inability to provide both time and frequency resolution restricted the effectiveness of frequency domain. The ideal assumption that has been made for stationary time series is not useful for bearing *FDi* practice since the waveform produced will be attenuated by noise and other factors. For machines under an unloaded condition, or unbalanced supply voltages, varying load, or load torque oscillations, the measured signals are generally transient and dynamic under the concerned time section. Therefore, analysis of the stationary quantities in some cases finds *difficult to monitor* or detect faults via either a pure *time-domain* or *frequency-domain* method. Due to the time-varying frequency spectrum of the transient signals, suitable time-frequency decomposition tools are needed for real-time monitoring and *FDi*. Nowadays, researchers shifted to the time-frequency domain to analyze the energy distribution of the frequency components through time transient signal since the needs of time localization of the spectral components. Thus, representations of time-frequency.

TFA can identify the signal *frequency* components, and reveal their *time* variant features, which has been an effective tool for monitoring by extracting feature information contained in non-stationary signals *(Feng et al., 2013).* In *TFA*, the energy of power spectrum of waveform signal will be resented in along both functions of time and frequency which better to reveal fault patterns for more accurate *FDi*. In the joint time-frequency domain, a *time-frequency representation* (*TFR*) maps a one-dimensional time series signal to a two-dimensional distribution function in both *time* and *frequency*, which shows the spectral variations over time. The joint *Time-Frequency Distribution* (*TFD*) is an important tool for analysis of non-stationary signals that can be found in various *FDD* applications in practice *(Antonino-Daviu et al., 2009; Feng et al., 2013).*

TFA methods have been widely investigated in the literature *(Gröchenig, 2001). Various TFA methods* have been proposed and applied to *system FM*. Among these methods, *STFT*, *WT*, *DWT*, *Wavelet Packet Transform* (*WPT*) *Hilbert-Huang transform* (*HHT*), and *WVD* are most common used.
STFT is one of the examples of time-frequency domain analysis which use a sliding window to produce a spectrogram. In another word, they will divide the signal into small segments where these small segments of the signal will be assumed to be stationary. The width of segmented signal and window must be related to ensuring the stationarity of the signal. Next, *FT* is applied on each small segment. The *STFT* efficiency depends on the scale and type of window used for analyzing the signal to obtain a good frequency resolution. *STFT* has some issue with the time and frequency resolution which makes the interpretation of signal is difficult. The *STFT* method suffers the high computational cost if it is required to obtain a good resolution. However, there is still a study using *STFT* is done by researchers.

WT was developed as an alternative method to *STFT*. *WT* is a mathematical tool which adjusts consecutive time series data signals in the time domain to time-frequency domain using different translation and dilation function called `mother wavelet'. *WT* decomposes signal into several scales at different levels of resolution and capable to analyze waveform data of bearing signal. As a linear decomposition, *WT* based method can provide a good resolution in time for high-frequency components of a signal and a good resolution in frequency for low-frequency components, which has demonstrated the effectiveness for tracking fault frequency components under non-stationary conditions *(Gritli et al., 2013).* Basic theory of *WT* as potential *FAn* tool can be found in several papers, *e.g., (Coifman, Wickerhauser, 1992).*
DWT decomposes the signal into mutually orthogonal set of functions which are generated by translations and dilations of a main analyzing function known as the mother wavelet. *DWT* decomposed signal into several levels comprised with the low pass approximation and high pass detailed coefficients where after first level only the detailed coefficient is decomposed further. The discrete decomposition can be made in pyramidal or packet mode. Usually, the *DWT* employs a dyadic (power of 2) grid and orthonormal wavelet basis functions exhibiting zero redundancy. However, *DWT* has several restrictions that limit its effectiveness for example shift invariances, aliasing, less directional selectivity, oscillation of wavelet coefficients and highly redundant representation that require higher computational cost.
Continuous Wavelet Transform (CWT) is able to work with every scale where the entire signal will be scaled and shifted over which sometimes lead to redundancy of information. Redundancy of information will consume a lot of time during *SP* even though large dataset is useful for signal de-noising and feature extraction. *WPT* analysis is a generalization of *discrete WA* providing a redundant decomposition structure. That means the decomposition is applied to both low pass results (approximations) and high pass results (details). Both detail and approximation signals are split at each level into finer components which offers the richest analysis.
WVD method features a relatively low computational cost and high resolution, as the entire signal is utilized to obtain the energy at each time-frequency bin, which has been successfully applied to the *FDi* along with current analysis *(Burnett et al., 1996)* or vibration analysis *(Tang et al., 2010).* A significant defect of the conventional *WVD* method is the appearance of the cross terms in the distribution of artifacts, which hinders the application of *WVD* methods. Very recently, via combining advanced notch *FIR* filters and the conventional *WVD* method, an improved *WVD* based *FDi* algorithm was proposed in *(Climente-Alarcon et al., 2014),* which can effectively minimize the cross terms and provide seamless high-resolution time-frequency diagrams enabling the *FDi* of rotor asymmetries and eccentricities in induction machines directly connected to the grid even in the worst cases. In *(Xiang, Yan, 2014),* a self-adaptive *WVD* method, based on local mean decomposition.

WT was applied to cables and transmission line faults using a model-based approach by transforming the voltage and current measurements to capture fault signatures *(Kim et al., 2002; Jiang et al., 2003a).*
(Germán-Salló, Strnad, 2017) applied *SWT* and *WPT* for *FDe*. They conclude that Wavelet packet decompositions are more flexible than the *DWT* and the *FT* because the basic functions that are used in a *DWT* are also available in the *wavelet packet decomposition*.
STFT method has been widely applied to detect both stator and rotor faults in inductor motors *(Nandi et al., 2013).* In *(Cabal-Yepez et al., 2013),* the *STFT* and discrete *WT* were integrated to do early *diagnosis* and *prognosis* of the abnormalities in the monitored industrial systems. It is noticed that *STFT* and *WT* may suffer some uncertain limitations. For instance, the selection of a suitable window size in *STFT* is required, but it is generally not known priori.
The type of the basic wavelet function in *WT* has a direct effect on the effectiveness in identifying transient elements hidden within a dynamic signal. However, on the basis of the instantaneous frequencies resulting from the intrinsic-mode functions of the signal being analyzed, *HHT* method is not constrained by the uncertain limitations with respect to the time and frequency resolutions suffered by some time-frequency techniques (*e.g.*, *STFT* and *WT*), which has shown quite interesting performance in terms of fault severity evaluation.

III.8.4 - Advantages and Drawbacks

The main advantage of the *SiBT*s of *FDe* is that a *MM* is not used in this approach; as such a model can be difficult and even in some cases impossible to derive.
However, the *SP* -based scheme is mainly used for processes in the steady state, and its efficiency for the detection of faults in dynamic systems, which are of a wide operating range due to the possible variation of input signals, is strongly limited. Furthermore, the main drawback is the need for data from the system when it is affected by faults, as these data should be used in the development of the database of fault scenarios. Moreover, it can be difficult to ensure robustness of the *FDI* algorithm based on signal models, as (according to theoretical considerations) all possible operation conditions should be tested before robustness is ensured. Some of these problems can solve by simulations, but then a model of a process is needed, undermining one of the advantages of the approach. So, the *SiBT* is most suitable for systems, which are difficult or in particular cases impossible to describe with a *MM*.

III.9 - Conclusion

This chapter presented a review of basic concepts and advances of *FDD* methods and the benefits and limits of each approach are pointed out. These methods are categorized as data-driven methods, *SiBT*s, knowledge methods and *MBT*s. Principles of different categories of methods are discussed and some algorithms are introduced. Their applications in industry and particularly in *NP*s have also been reviewed. The survey shows that different types of *FDD* methods have properties desirable for different types of problems. Since an industrial system usually contains components of great diversities, *FDD* system needs to deal with potentially diverse types of fault scenarios. Some solution approaches may perform better than the others due to the difference in the problem formulation. Therefore, selection of *FDD* methodology is dependent on the behavior and feature of applications. Tools for *FDD* should be selected from the variety of choices such as the availability of data and knowledge on the process, and the technical and economic considerations.

While desirable characteristics are defined for a well-designed approach, nevertheless, according to the comprehensive review by *(Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c),* it is apparent that no individual method can provide robust performance alone and no single approach is adapted to all the requirements for a *FDD* system. Each method has own advantages and limitations and is effective in detecting only a certain kind of failures. Perfect method does not exist and there doesn't exist any single technique that can completely identify all possible types of failures.
A framework for solving problems in a collective way, using different and parallel reasoning as hybrid methods, have been proposed by many researchers to overcome these handicaps of the individual methods and they proved to be an attractive alternative. These methods are constructed using two or more independent *FDD* methods which enable to integrate the advantages of different individual methods *(Das et al, 2012)* and improve the monitoring performance.

Because of extensive current research activity in supervision field, it was not possible to provide and cover all comprehensive representation of the scene. We have therefore focused on basic concepts in the existing theory and may gain some relevance for future research and practical applications.

CHAPTER IV

Fault Supervision with Artificial Neural Networks

In the context of complex processes, the generation of an appropriate mathematical model is a real challenge that what we will see in in the next chapter. One solution is to use NNs as an alternative method particularly, when the knowledge of the process is not sufficient or not present at all.

Therefore, our goal of this present chapter is to describe a strategy for detecting and identifying, as early as possible, the failures and abnormal situations resulting from malfunctions of the monitored process by using NNs and, historical and online data acquired during the system operation. At first, we describe the elementary structure of NNs and their fundamental categories, and then we explain the different manners applying these NN types to the supervision of faults.

IV.1 - Introduction

Methods based on *NNs* are researched widely over the past decades. Nowadays, the *NNs* have been rapidly developed and successfully applied to solve challenging problems with good results in a *large variety*, almost all branches, of *science*: *research field, e.g., SP, classification, prediction, modeling, process identification; optimization, filtering*; process *engineering, e.g., image processing, PR* *(Chetouani, 2008);* and *technology, e.g., monitoring* and *control* of dynamic system in industrial plant *(Ge et al., 2009), medical diagnosis* *(Campa et al., 2008; Mandal, 2015).*
NNs have been successfully *applied* to *many areas* involving *nuclear* and *chemical reactor* since the late *1980's* *(Bueno et al., 2012).* First *applications* of *NN*s for *FM* in *chemical* *(Hoskins, Himmelblau, 1988)* and *NR* *(Yiftah, 1988)* have demonstrated the potential to give important solutions. *(Uhrig, Guo, 1989)* published the first results in *TI* in *NPP*. Since the early 90's a plethora of computer systems based on *NN*s have been proposed for *NPP* monitoring, see *(Reifman, 1997b)* and references therein. Nowadays, the vast number of applications has increased significantly.

The use of *NNs* is considered when the knowledge of the process is not sufficient or is not available at all. *NN is* applied for process *CM* where the focus is on small irreversible changes in the process which develop into bigger faults *(Srivastava et al., 2014).* When developing *NN* models, the only required knowledge is usually the process input and output *data*. In many *FM* problems of physical systems, such as *NPP*, the inputs to the *NN*s usually are *S/D measurements* and each *output neuron* is a process *alarm* corresponds to one particular *fault* possibility. In such monitoring applications, the network must be able to handle *continuously* the *input data* and the learning must be *supervised*. The input variables can be *quantitative* (*e.g.,* output of *S/Ds*), and/or *qualitative* (*e.g.,* observations made by the operators). From these input variables, *NNs* give outputs which can be an *estimation* or *classification* of monitored parameters.

NNs have been rapidly developed and successfully applied in a *large variety* of research *field* in almost all branches of science (*e.g. SP, PR, process identification, etc*.), engineering applications including *image processing, PR* and technology (*e.g. monitoring* and *control* of dynamic system in industrial plant; *medical diagnosis*, *etc*.) with good results. Nowadays, among these applications, *NNs* have been widely used as a powerful intelligence-based technique and have become a sort of ideal tool for *FM* issues and *accommodation* schemes using the history of a system's generated data. *(Haykin, 1999)* gives a general theory of *NNs* and includes application areas. Using *NNs* for monitoring is not only considered as alternative to traditional methods, but also, they have an important feature. The major *capabilities* and *advantages* of *NN*s allow them when applied to *FM system* to be *robust*, *noise tolerant* and applied in *real time* which represent an important solution for *CtM* of *plant parameters*, *instruments*, *equipment, systems* and *process.* Therefore, *NNs* are *ideally* appropriate as a candidate for *FM*, *control*, and *risk evaluation* in *NPP environments*.

In many cases, it is necessary to employ more robust techniques. Many methods *driven by data* *(Nelles, 2001)* had been proposed for monitoring a *complex NL processes* (such as *NP*s), to overcome some of the difficulties of using *MMs* (*e.g., real-time response,* the accurate *MMs* are too difficult or too expensive to get), to make *FDI* algorithm's more applicable to real systems and when it is necessary to use more robust techniques. Among these methods, we find the *NNs* approach *(Fuente et al., 2012; Fuente, Sainz-Palmero, 2014).* The ability of *NN* to identify *complex NL system* without the needs of any physical knowledge of the system itself makes *NN* one of the most popular *black-box models*, once it has been trained to recognize the various states of the system. So, in this case, the *NNs* can be used to both *residuals generation* for *FDe,* and *residuals analysis* and *evaluation* for *isolate faults*. In this case, *NNs* only takes one cycle to detect specific conditions *(Taghadomi-Saberi et al., 2013; Kalogirou et al., 2014).*

IV.2 – Neural Networks

The origin of the inspiration of *NNs* goes back to 1890 when *W. James*, American psychologist, introduces the concept of associative memory. He proposes what will become a working law for the learning of *NNs*, later known as *Hebb's* law. *NN* concept was first proposed by *(Mcculloch, Pitts, 1943)* under the name: *formal neuron* and later, it has been subject matters among the researchers around the world after the introduction of a first *NN* training algorithm by *(Rosenblatt, 1958).*
NN concept was first proposed by *McCulloch* and *Pitts* in 1943 under the name: *formal neuron (Mcculloch, Pitts, 1943).* Later, the *NN* has been subject matters among the researchers around the world after the introduction of a first *NN* training algorithm by Rosenblatt in way back 1958 *(Rosenblatt, 1958).* The concept of *NNs* was inspired from *neurobiology*, and attempts to mimic the function and structure of the *human brain*. Therefore, a great deal of the terminology is borrowed from neuroscience. However, *NNs* are extremely simplified compared to the complex behavior of biological neurons. In literature, we find others names for *NNs*, such as *connectionism*, *parallel distributed processing*, *neuro-computing*, *natural intelligent systems*, *ML algorithms*, and *so on (Santosh et al., 2007).* In literature, we find others names for *NNs*, such as *connectionism*, *distributed parallel processing, neuro-computing, natural intelligent systems*, *ML algorithms*, and *so on*.

*NN*s are mathematical algorithms and promising *learning technique.* A *NN* is a highly complex *NL* and adaptive system made up of *parallel* interconnections with different strengths (*weight*) between a large numbers of elementary *processing units* called *artificial neurons,* often just simply called *neurons,* or *nodes* of the same structure to perform predetermined *functions*. These *neurons* are grouped into *layers* which constitute the *neural structure* and gives power for neural computation. It has the ability to keep experimental knowledge and making it available for use. This knowledge is acquired by the networks through a learning process from example which allows him improving its performance and adapt to changes in the environment. *NNs* map sets of input data onto a set of appropriate outputs. So, the *goal* of *NNs* application is to find the complex relationships between the input and the output variables. This is accomplished by adjusting the weights set through a learning process to allow the overall network to produce appropriate results.
A lot of different models of *NN*s have been developed till now. Currently, there is no simple way to determine the best *architecture*. Each network type has *advantages* and *disadvantages*; the aptness of a type with regard to others is strongly bound to the considered application. So, experience is the only key factor to determine whether it is the best or bad architecture.

In viewing *NNs* structures and architectures, we can be classified them mainly into *FF,* called also *Static Neural Networks* (*SNNs*), and *Temporal Neural Networks* (*TNNs*) categories according to the nature of used neurons (*i.e. static* or *dynamic neurons*) and how they are connected (*Figure IV.1*) *(Racoceanu, 2003; Zemouri, 2003; El-Shafie, Aminah, 2013; Beale, 2017).*

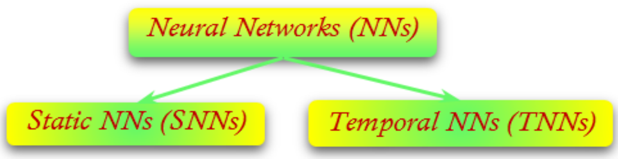


Figure IV.1 - Classification of NNs: static and temporal.

Other popular *NNs* classification can be found in *(Ham, Kostanic, 2001). Static networks* were *the first* and *simplest type* of *networks*. As the name indicates, they do not incorporate any feed-back *(Sinha et al., 2000; El-Shafie, Aminah, 2013; Beale, 2017)* and do not possess any time delay units. Their outputs are calculated directly from the input through *FF* connections *(Majumder et al., 2012; El-Shafie, Aminah, 2013; Beale, 2017).* In temporal networks, the output depends not only on the current input to the network, but also on the previous inputs;

current or previous outputs, or states of the network *(Chiang et al., 2004a; El-Shafie, Aminah, 2013; Beale, 2017).* For more details on static and temporal *NN*s, see *(Gupta et al., 2003).*

IV.2.1 - Neuron model

In a *NN*, each *neuron* can be considered as a mathematical function. It receives *weighted* multiple inputs which are summed and added to the *bias*. The total value is processed through an *activation function (Ruineihart et al., 1985; Gupta et al., 2003)* called also *transfer (Gaya et al., 2014; Shahbazi et al., 2016)* or *transmission function (Rezaei et al., 2015)* to generate at the end a single output as is illustrated on *Figure IV.2*. This conventional neuron, called sometimes *static neuron (Mohammadi et al., 2010),* ignores many of the characteristics of its biological counterpart, and is a grossly simplified version.

So, the *MM* of neuron output is presented by:

$$z = f(s),\ s = \sum_{i=1}^{n} w_i x_i + w_0 x_0 \tag{IV.1}$$

where $(x_1, x_2, \ldots, x_n)$ are inputs from layers neurons; $(w_1, w_2, \ldots, w_n)$ are the corresponding *weights*; $w_0 x_0$, denoted usually by b, is the *bias* also known as *threshold* of the neuron which can be *positive, zero* or *negative.* It has the effect of increasing or lowering the summation result (*i.e.* the input of the activation function), depending on its sign; f is a *NL activation function* and its input s is named *induced local field* or *activation potential*; n is the *number* of input connections to the current neuron, and y is the *output* of the neuron. The role of *weights* is controlling the rate of passage of signal. So, they are crucial because they allow modifying the relative importance or strength of connections between neurons. The *activation function* has a task to limit the amplitude of the output of a neuron. There are several types, *linear* and *NL*, of *activation functions* in which *Sigmoid (Cybenko, 1989)* have been the first proposed and most used transfer function. Others type have been proposed like *unit step* or *threshold*, *Gaussian*, *Lorentzian*, *plane wave*, and *rational fraction*, *etc.*

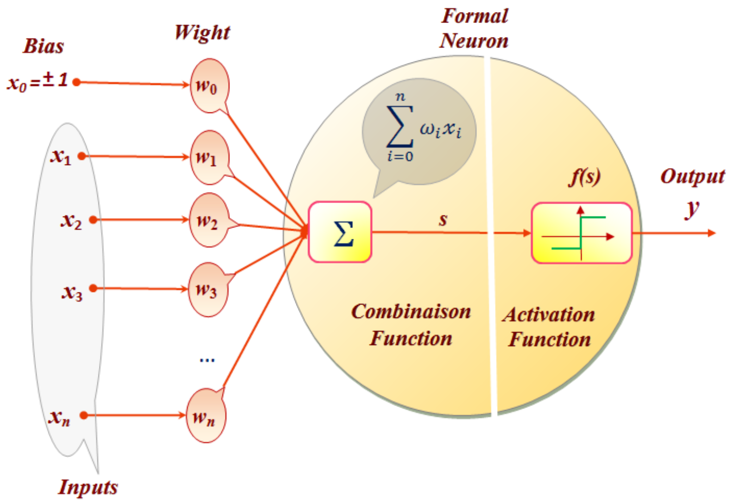


Figure IV.2 – Basic architecture of a static artificial neuron (Gupta et al., 2003).

Beside *static neuron*, *dynamic neuron* units *(Racoceanu, 2003; Mohammadi et al., 2010)* considered as the basic of the *DNNs*, receive not only external inputs but also state feedback signals from themselves, its outputs, its synapses or other neurons (*Figure IV.3*). Some other dynamic neuron structures are given in *(Gupta et al., 2003; Tayarani-Bathaie et al., 2012).*

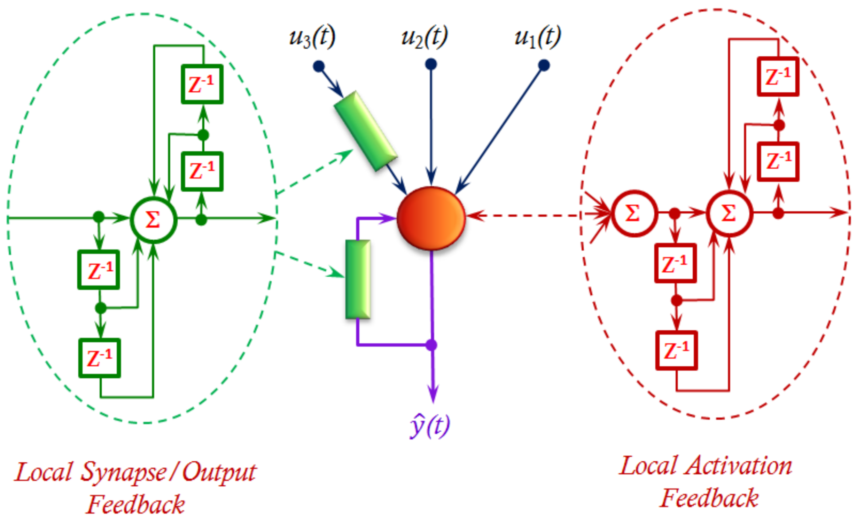


Figure IV.3 – Different representation of internal dynamics at the neuron (Frank et al., 2000a).

IV.2.2 - Static Networks

FFNN, called also, *SNN*, was the first and simplest type of *network*. *FFNN* respond instantaneously to the inputs, for they do not possess any time delay units. *FFNN* consists of three layers: *input layer*, one or more *intermediate layers* and *output layer*. Layer is a group of units not connected between them. So, there is no a recursive in the connections inside the same layer. Layers are connected such that the signal (*i.e.,* data or information) fed on the input layer can pass (propagate) forward (*i.e.,* only in one direction) *(Patel, Yalamalle, 2014* through the *intermediate layer* (*s*) and reach the output layer to generate the exits *(Zhou et al., 2003; Patel, Yalamalle, 2014*. Every neuron in a hidden and output layer receives its inputs from bias and whited output neurons in its precedent layer and sends its output to the neurons in its subsequent layer. So *FFNNs* respond instantaneously to the inputs *(Tatem et al., 2002; Ahsan, Hassan, 2013)* and are conditionally stable.

The first layer represents the input layer which receives the external information (*i.e.* input data) and each its neuron corresponds to an input variable. The output layer where the desired output values received from the outside world and the calculated values are presented to the environment. *Output layer* has the same number of neurons as a size of output signal of the network. *Intermediate layers* collect information from the input layer in each of their neurons. These layers are commonly known as *hidden layer* since the neurons (*hidden neurons*) in this layer are essentially concealed from view *(Patel, Yalamalle, 2014* and they do not converse directly with the outside world *(Mandavgane, Pandharipande, 2006).* Therefore, the hidden layer neurons and the bias neuron are fully connected to the output neurons. So, the role of the *hidden neurons* is to link the external inputs to the network outputs by performing a mapping between them in a *FF* arrangement *(Jain et al., 2015).* The hidden layer is used to characterize the *NL* properties of the system to be analyzed and many researchers believe that the hidden layers of a *NN* act as feature extractors. Hidden layer size (*i.e.,* number of hidden neurons) and number of hidden layers should be optimally determined *(Jayawardena, Fernando, 2001; Patra et al., 2010)* because they influence on the performance of the trained network. They are one of the important issues in the development of the network architecture and the success of many *NN* applications *(Chiang et al., 2004a).* Choosing the best number of layers, special attention should be paid to the "curse of dimensionality" *(Hastie et al., 2003).* The *NN* model with *one hidden layer* is *used frequently (Gowri, Mary, 2016).* However, *NN* model with *multiple hidden layers* is used to *solve complex problems* and the number of neurons in the hidden layer is totally dependent on the complexity of the process, the optimum network structure did not necessarily consist of the highest number of neurons but it is apparently based on the structure that effectively captured the system's complexity. *(Minns, Hall, 1996)* state that an alternative approach might be to increase the number of neurons in the hidden layer rather than to add another layer to the network and a single hidden layer should be sufficient for the majority of real-world applications. However, one hidden layer may require a very large number of hidden nodes, which is not desirable because the training time will increase and the network generalization ability will worsen. *However*, *NN* model with *multiple hidden layers* is used to *solve complex problems (Gowri, Mary, 2016). (Abrahart, See, 2000)* indicate that the use of two or more hidden layers might not substantially improve the network performance but only add delay to the training time. There are a number of studies indicating that one or two hidden layers would generally have better convergence, because more than two hidden layers would result in the ability of convergence to reduce gradually and produce many local minima *(Chiang et al., 2004a).* Using *additional* levels of *hidden neurons* lead to increase flexibility, more processing accuracy and converges the *NN* faster, but this comes at the cost of the *generalization* capabilities reducing (*i.e.* the *NN* responds poorly to test patterns never used in the training) *(Wilamowski, 2011)*, complexity increasing in the training algorithm (*e.g.* increase the training time) without significant improvement in training results, and *over-fitting (i.e.* inability to capture the underlying relationships in the data) can occur. So, using *more hidden* neurons than necessary is *wasteful*, as a *less* number of neurons would serve the desired performances just fine *(Patel, Yalamalle, 2014; Simsir et al., 2016).* In general, networks with fewer hidden nodes are preferable as they usually have better generalization capabilities and less over-fitting problems. The computational time required is also less with a smaller number of nodes. On the other hand, *(Haider, Zeng, 2009)* indicates that using less hidden neurons than required may have insufficient degrees of freedom to capture the underlying relationships in the data which impaired the performance of the network *(El-Shafie, Aminah, 2013; Patel, Yalamalle, 2014).*

Determination of the appropriate structure and parameters of the *NN* model in the presented way is a complex task. Furthermore, an arbitrary selection of the *NN* structure can be a source of the model uncertainty. Thus, it seems desirable to have a tool which can be used to the automatic selection of the *NN* structure, based only on the measured data. Besides the type of *NN* we have to define, the determination of minimum (optimal) number of necessary hidden neurons and hidden layers is a crucial yet complicated one *(Simsir et al., 2016).* This is typically done by cross validating different *NN* structures. It is completely practical and there is no theoretical basis for selecting these parameters, although a few systematic approaches have been reported. Since, there is not a systematic or standard way to select the size and number of hidden layers, the best and most common way to decide is by *trial-and-error* with the help of some guidelines *(Chiang et al., 2004a; El-Shafie, Aminah, 2013).* A rule of thumb is that the number of samples in the training set should at least be greater than the number of synaptic weights *(Tarassenko, 1998).* This gives the upper limit of the number of nodes for the network *(Jayawardena, Fernando, 2001; Patra et al., 2010).* Moreover, the *structure* and *behavior* of a *SNN* is determined by the *transfer function*; the *number and* the *size* of *hidden layer* (number of neuron within); and *learning algorithms* that determine how the weights are adjusted which all participate to the performance determination and to the choice of the best *NN architecture* for a given application. The operation of the *SNN* can be divided into two steps: *feed forward* and *back-propagation.* In the *feed forward step*, an input pattern is applied to the input layer and its effect propagates, layer by layer, through the network until an output is produced. The network's actual output value is then compared to the expected output, and an error signal is computed for each of the output nodes. Since all the hidden nodes have, to some degree, contributed to the errors evident in the output layer, the output error signals are transmitted *backwards* from the output layer to each node in the hidden layer that immediately contributed to the output layer. This process is then repeated, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the overall error.

Four *static networks* are well-*known: MLP network*, *RBF networks*, *AANN Kohonen's Networks* and *PNNs*. The last one is not treated seen the limited space.

IV.2.2.1 - Multilayer Perceptron

MLPs are currently the most commonly used neural structures in technique. This fact results from the simplicity of their implementation in programmable systems, as well as the mapping capabilities of any function. The *MLP* is an abbreviation to *MLP* which is a simplification of *feed forward multilayer perceptron network,* also called *feed forward multilayer network (Reifman, 1997a).* It is considered as an extension to the *single-layer perceptron (SLP) (Zemouri, 2003)* which is the most influential work done in the development of *NNs* in the mid-1960s. It is based on *supervised* learning *(Da Siva et al., 2017)* and uses one or more hidden layers between input and output layer. *Figure IV.4* shows a typical *MLP* that consists of *three layers* which are an *input layer* with three inputs, one *hidden layer* and an *output layer* with two outputs. All neurons in each layer are fully connected to every neuron in the succeeding layer. For simplification, the *bias* levels at each neuron have been omitted for convenience of presentation (this is applicable throughout the rest of this document). The *MLP* provides, at each output node, a *linear combination* of the outputs of the hidden-layer neurons *(Kaminski et al., 2011; Kannan, Rathinam, 2012).* Many different activation functions are used in the *MLP*. *Sigmoid functions* are usually used for *hidden layer neurons (Zayandehroodi, 2010; Ngaopitakkul et al., 2011, Skowron et al., 2019b)* and *linear activation function* for the *output layer neurons (Zayandehroodi, 2010; Ngaopitakkul et al., 2011).* The fundamental and the most widely applied training algorithm for the *MLP* is the *Levenberg-Marquardt* (*LM*) *gradient algorithm (Skowron et al., 2019a),* the *gradient descent in error*, *error BP* or simply *back-propagation, BP,* learning algorithm *(Atkinson, Tatnall, 1997).* So, the *MLP* is usually called *BP network (Uhrig, Guo, 1989; Perez et al., 2016).*
(Alsmadi et al., 2009) concluded that the *BP* learning algorithm is the best algorithm applied to *MLP* which allowed exceeding the limits of simple perceptron. It could be argued that the *MLP* architecture is the *most popular* choice for *NN* applications *(Wilamowski, 2009; Wilamowski, 2011).*

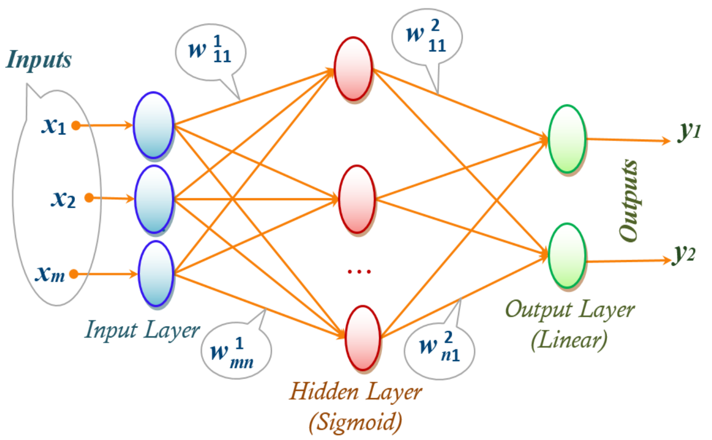


Figure IV.4 - MLP with one hidden layer, 3 inputs, 2 outputs n neurons in hidden layer.

MLP is used in many applications to solve some problems that a *SLP* is not able to do *(Hoskins, Himmelblau, 1988).* The *MLP* is the most common and popular choice for *NN* applications, widely studied and, frequently used and applied, class of network architecture today. *MLP* are often used to approximate unknown functions from their inputs to outputs. *MLP*'s capability of approximating any continuous function with support in the unit hypercube with only single hidden layer and sigmoid activation function was first proved by *(Chappelier, Grumbach, 1996).* *NNs* of *multi-layered perceptron* type are essentially *semi-parametric regression estimators* and well-appropriate for this purpose, as they can *approximate* virtually any (measurable) *function* up to an arbitrary degree of *accuracy*. In *(Wei, Chaudhary, 2015),* it was shown that an *MLP* with at least one hidden layer is able of approximating any *NL* function once enough training is provided.

Nevertheless, despite its popularity, *MLP* architectures require more neurons, to solve a problem, than other architectures *(Wilamowski, 2009; Wilamowski, 2011). MLP* architectures require more neurons. Although increasing the number of neurons converges the *NN* faster, the network loses its generalization ability *(Wilamowski, 2009; Wilamowski, 2011).* It also suffers of numerous drawbacks, as long learning time, a sensibility on initial weight conditions, and probable presence of local minima *(Mamar, 2008; Patra et al., 2010).* Therefore, this architecture is neither *powerful* nor *efficient,* in comparison to other *SNN* architectures *(Guo, Musgrave, 1995; Samy et al., 2010; Wilamowski, Yu, 2010).*

IV.2.2.2 - Radial Basic Function Network

The use of the *RBF, networks* dates back to the 1970s *(Schagen, 1979)* to solve multi-variable interpolation problems. The theoretical bases of these networks were then deepened by *(Powell, 1987; Poggio, Girosi, 1989).* Other works have followed each other where the application of *RBF* has been extended to other areas, namely the prediction of the evolution of dynamical systems and the classification of phenomenon. The *RBF network (Rumelhart, McClelland, 1987)* is a special, *important class* and the most commonly used type of *MLP* network. It has a very simple architecture *(Kaminski et al., 2011; Kannan, Rathinam, 2012)* with different characteristic topologies. In *RBF*, the *Gaussian function (Matic et al., 2010a; Yi, 2010)* is mostly applied as an *activation function* in *hidden* neurons *(Ngaopitakkul et al., 2011; Kannan, Rathinam, 2012; Heger, 2015).* Thus, the *RBF network* is different than *MLP network activation functions* in the *hidden layer (Kaminski et al., 2011).* The particularity of these networks lies in the fact that they are able to provide a local representation of space through *RBFs,* whose influence is restricted to some area of this space, represents the *Euclidean norm*. *Hybrid learning* algorithm for training the *RBF network* converges much faster than the *BP algorithm* for *MLP* training. So, *RBF network* has the *advantage* that *local minima* are avoided, but it has the *disadvantage* of requiring good coverage of the input space. Furthermore, the *RBF network* has a very good robustness property and in recent years, it has been enjoying greater popularity as an alternative solution to the slowly convergent *MLP*.

IV.2.2.3 – Auto-Associative Network

Beside the *MLP and RBF networks*, other *SNN*s are well known; basically, *AANN* is one special type and the most frequently used network structure, first proposed by *(Kramer, 1991)*. The *AANN* has a symmetrical topology composed of *five layers.* Input layer, three hidden layers (*mapping layer*, *bottleneck layer*, *de-mapping layer*), and an output layer with *bottleneck layer* is the middle layer (*Figure IV.5*). The use of the three hidden layers in the structure of the *AANN* as opposed to one hidden layer is due to the need for data compression inside the network in order to filter out both noise and biases. The *AANN* should be viewed as a cascade combination of *two single-hidden layer networks* (*two independent three layer NNs* connected in series). The first network mixes and compresses the *n* redundant measurements into a smaller number of characteristic variables which should ideally represent the essential characteristics of the process. The second network works in the opposite way and uses the compressed information to regenerate the original n redundant measurements. The *mapping* and the *de-mapping layers* have the same number of neurons and the size of the *bottleneck layer* should be smaller than the other hidden, input or output layers. The outputs are trained to reproduce the output identical to its inputs therefore, an *AANN* have a unit overall gain *(Xu, Hines, 1970).* The bottleneck layer has linear activation functions. The *de-mapping layer* has the same activation functions as the mapping layer which can be sigmoidal, tangent hyperbolic, or any other similar nonlinearities.

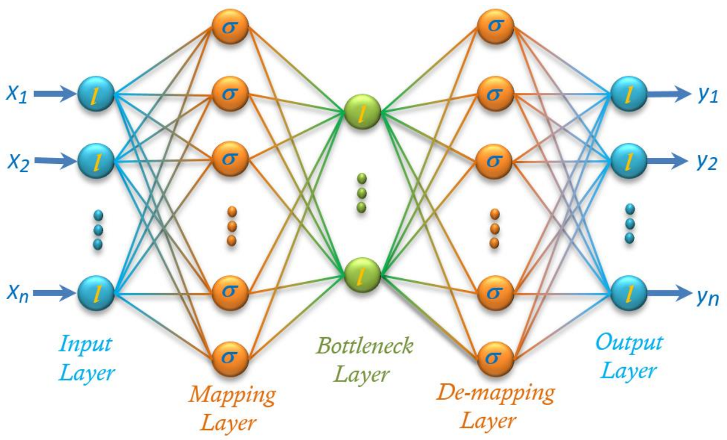


Figure IV.5 - AANN architecture (Shah et al., 2013) where σ denotes the sigmoidal nodes (tan-sigmoid transfer functions, and l denotes the linear nodes.

The *bottleneck layer* (*hidden layer*) plays important role in the effectiveness of the network. It has a dimension. It prevents a simple one-to-one mapping as result of training and the least-square training criterion assures that the internal representation developed by the network contains the maximum information it can accumulate with the existing structure. Therefore, the bottleneck layer output is the compressed representation of the data given in the input layer and the output of the nodes in the bottleneck layer can be viewed as *principal components* (*PCAs*). So, the *AANN* is motivated from and based on the concept of *PCA* that it can deal with both linear and nonlinear correlations among the variables and produce a compact and concise data representation. The minimum number of nodes in the bottleneck layer that will provide sufficient information for data recovery represents the degree of freedom of the data system. So, the size of bottleneck layer is critical to obtain the desired effect of eliminating the redundancies in the measurements. The goal of *AANN* is not simply copying the inputs to the outputs (this would be trivial), but instead of this, it is to eliminate the redundancies and extract the key features in the input data. This is done by compressing these data at the bottleneck layer into a set of new and uncorrelated variables in the new space having reduced dimensionality *(Kramer, 1992)* in order to learn a correlation model of the input data, and removing noise at the output layer.

The *auto-associativity* has the *advantage* of *detecting* unknown plant *conditions*. *AANN* based models are much faster and assuming optimal training, they are more reliable too. On another hand, one more important feature of *AANN* is that it plays the role of noise reduction (filtering) *(Mathisen, 2010).* Enhanced training performance due to noise filtering phenomenon of *AANN* with plant signals is reported in the literature *(Ciftcioglu, Türkcan, 1998)* and it is termed as robust training *(Wrest et al., 1996).*

AANN allows predicting outputs based on what it learned. One of its interesting aspects is that the network is trained with the same inputs and targets and thus the network is performing an identity mapping in which the output layer is providing an approximation of the inputs. Therefore, the auto-associativity has the advantage of detecting unknown plant conditions. Furthermore, this network is suitable to formulate *NL PCA* on a given data set. The network has been used by some researchers for sensor *FDe* in gas turbines *(Lu et al., 2001; Ogaji et al., 2002).* The *NL* mapping and de-mapping provides that, in such multivariate plant monitoring, the network can be much more sensitive to process changes, and may help to highlight incipient problems (early *FDe*) before they become obvious yielding serious problems.

Recently, different *AANN* approaches have been developed in the field of sensor *FDD*. The motivation is due to the capabilities of these networks in providing a robust identity map between their input and output. *(Mousavi H. et al., 2017)* presented a novel algorithm called *Self-Reconstructing AANN* (*S-AANN*) which is able to detect and isolate single faulty sensor via reconstruction. The algorithm is extended to be applicable to multiple fault conditions. So, this algorithm appropriate candidate for online applications. *Hines, Uhrig, 1998)* applied the *AANN* method to detect faulty sensors. The authors in *(Guo-Jian et al., 2010)* proposed a sensor *FDe* and repair methodology based on *AANN* to detect multi-faulty transducers of an *IEEE* 1451 based intelligent sensor synchronously. The work in *(Najafi et al., 2004)* identified a single fault sensor using an enhanced *AANN* and the exact value of the fault sensor was reconstructed. The authors in *(Guo et al., 2003)* used *AANN* for *SeV* of rotor speed measurements in the engine control loops. *(Rao, 2009)* proposes of *AANN* architecture for sensor data computation, *FDIso*. *(Böhme et al., 1999a)* have compared the potential of *AANNs* and *SOM* network for signal *FDe* and reconstruction. *(Vanini, 2014)* have proposed *FDIso* scheme based on the *MuM* approach based on a bank of *AANNs*. This methodology provided a novel integrated solution to the problem of both sensor and component *FDIso* even though possibly both engine and sensor faults may occur concurrently. Moreover, the proposed algorithm can be used for sensor data validation and correction as the first step for health monitoring of jet engines

IV.2.2.4 – Kohonen Network

Kohonen model is another well-known *SNN* type called *Kohonen SOM* or simply *SOM* *(Böhme et al., 1999a; Tan et al., 2009).* The *SOM* was first proposed by *(Kohonen, 1990)* as *competitive* type of networks *(Freeman, Skapura, 1992)* and a specific type of *unsupervised NN* based on three major steps: *competition*, *co-operation* and *adaptation* *(Kohonen, 1997; Araújo, Barreto, 2002).* *SOM* maps the multi-dimensional space onto a two-dimensional space such that the original order is preserved. The *SOM* algorithm is a hybrid method in that it combines the goals of projection and clustering algorithms. It can be used at the same time to visualize the clusters in a data set, and to represent the set on a two-dimensional map. Furthermore, *SOM* is a mean for automatically arranging high-dimensional data. So, it is used particularly in classification patterns. *SOM* is an unsupervised learning algorithm of *NN*, which is presented to solve the *FDD* problem.

In the *SOM* network the neurons are *arranged* in two layers: *input* layer and *output* layer (*Figure IV.6*). The output layer also known as the *competitive* or *Kohonen layer* is organized as one, two (the most common), or three dimensional *(Haykin, 1999).* In the case of 2*D* representation, a *rectangular* or *hexagonal* map can be used. A *toroidal* or *cylindrical* map could be used in case of 3*D* representation. The *input layer* is fully connected to the *output layer*, *i.e.,* each unit in *competitive layer* is connected to every unit in the input layer by a weighted connection or weight vector *(Foody, 1999).* The *Kohonen*'s units are interconnected with their local neighbors, and these connections could be excitatory *(Kohonen, 2001).*

The *SOM* is a mean for automatically arranging high-dimensional data sets quickly and availably. It projects the high-dimensional input data into a lower dimensional output map *(Kohonen, 1995).* Thereby, it is able to convert complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low dimensional display *(Vesanto, Alhoniemi, 2000),* while preserving the topology structure of the data *(Kohonen, 1997).* Therefore, *SOM* is considered an effective tool for *feature extraction, similarities display* and *classification* of high dimensional data. *Kohonen*'s network is not as successful as *MLP* and *RBF,* but its capacities of *auto-adaptation* (*non-supervised learning*) are much appreciated *(Vesanto et al., 2000).*

The *SOMs* are very often used in other problems of the analysis of large data structures *e.g.* in the problems image processing *(Amerijckx et al., 2003; Teng, Chang, 2012)* and robotics *(Barreto et al., 2003; Johnsson, Balkenius, 2011).* In recent years, they have gained popularity as an alternative to *PCA* for complex industrial processes *(Chen, Yan, 2012).* *SOM* surpasses *PCA* as a nonlinear dimensionality reduction technique. It is able to capture the nonlinear variations of the process and visualize them on a low-dimensional display in a topologically ordered fashion *(Kowalski et al., 2003; Chopra, Vajpai, 2011; Gonçalves et al., 2011).* The following Example is generated from a Java applet developed by *(Mirkes, 2011)* to illustrate the comparison between *PCA* and *SOM* based process monitoring.

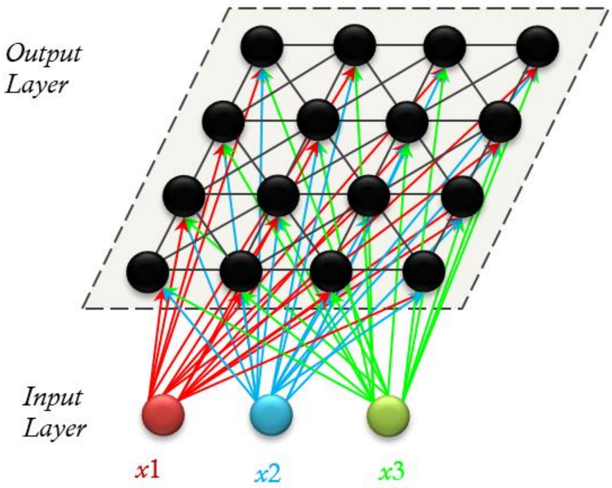


Figure IV.6 - Basic SOM structure.

The *SOMs* have been successfully applied in various engineering fields *(Kohonen et al., 1996)* including process and system analysis, *FDe*, voice recognition, robotics, and *PR*. The *SOMs* have been used in time series forecasting *(Lendasse et al., 2003; Simon et al., 2005; Hsu, 2011)* and they raising much interest recently, since, besides giving better results than the prediction approaches based on *MLP* or *RBF*. *SOMs* were investigated for early *FDe* capabilities in *(Sirola et al., 2009)*. They are applied in *FDD* *(Chan et al., 2001*; *Jämsä-Jounela et al., 2003; Seera et al., 2013)* and they have demonstrated good performance for *FDD* in induction machines *(Wu, Chow, 2004)*, with *(Elissa et al., 2011)* concluding that *SOMNNs* generally provide better solutions than other *SNNs* for this application field. *SOM* has been successfully used in process monitoring because of its ability to aggregate clusters of input information from raw data and project these data on a simpler two- or three-dimensional networks, resulting in relatively comprehensible visualizations *(Chen, Yan, 2013)*. The self-organizing feature map (*SOFM*) *NN* model is one of the best-known clustering techniques with unsupervised learning rules *(Park et al., 2003; Amarowicz, Katunin, 2014)*. *SOM* is widely used in data clustering and forms clusters by a self-organized collection of similar grids on the competition layer. The *U-matrix* represents the distances between each *Kohonen's* unit and its neighboring units and can reveal the local cluster structure of the map *(Ultsch, 2003)*. Distinct clusters in a given data set are easily identified using the U-matrix. The *SOM*-based *classification* is attractive, due to its topology preserving properties for solving various problems that traditionally have been the domain of conventional statistical and operational research techniques *(Melssen et al., 2006; Bianchi et al., 2007)*.

(Chen, Yan, 2012) proposed a novel *FDi* method which combines *SOM* with *correlative component* (*CCA*) is in order to visualize the occurrence of the fault clearly. Based on the sample data, CCA can extract fault classification information as much as possible, and then based on the identified correlative components, *SOM* can distinguish the various types of states on analysis the output map. The results show that the *SOM* integrated with *CCA* method is efficient and capable for real-time monitoring and *FDi* in complex chemical process. *(Gonçalves et al., 2011)* proposed a scheme based on *SOM* for *FDD* and *Temporal Kohonen Map* (*TSOM*) for fault prediction. *(Yu et al., 2014)* proposed a *SOM* based methodology for *FDD* of processes with nonlinear and non-Gaussian features. *(Xinyi, Xuefeng, 2013)* proposed a novel *FDi* method which combines *SOM* with *FiDiAn* in order to get a better visualization effect. *FiDiAn* can reduce the dimension of the data in terms of maximizing the separability of the classes. After feature extraction by *FiDiAn*, *SOM* can distinguish the different states on the output map clearly and it can also be used to monitor abnormal states. The result shows that the *SOM* integrated with *FiDiAn* method is efficient and capable for real-time monitoring and *FDi* in complex chemical process. It is a promising approach to catch a preliminary overview on intricate data sets. The *TSOM* derived

from the *SOM algorithm* is used for time series prediction *(Kohonen, 1997).* A *two-level SOM network* augments the conventional *SOM* network with an additional *one-dimensional Kohonen layer* in which each neuron is connected to neurons in the previous *Kohonen layer*. It is a promising approach to catch a preliminary overview on intricate data sets *(Nourani et al., 2016).*

IV.2.3 - Temporal networks

During the last years the use of *NN*s in dynamic systems modeling has increased significantly. This is justified by its feature listed above. Some applications of *NNs*, like monitoring and safety, require architectures able to treat the *temporal* aspects. Therefore, *TNNs* have been recently attracting great attention from the scientific community because they are really useful for *temporal processing*, *DSP*, *system identification* and *spatio-temporal pattern recognition.* Time factor plays a big role in the processing of dynamic systems and offer better computational capabilities compared to those of static counterparts *(Sinha et al., 2000). TNNs* offer this possibility of taking into account the temporal aspect of the data and thus perform temporal tasks performance. *TNNs* have dynamic capabilities to generate and process temporal information. They are more versatile and provide the strong capability to store an internal state and consequently process sequences of inputs *(Tayarani-Bathaie et al., 2012; Abed et al., 2014; Kuna, 2015).* In *TNNs*, the output depends not only on the current input to the network, but also on the previous inputs, the current or previous outputs or states of the network *(Chiang et al., 2004a; El-Shafie, Aminah, 2013).*

Taking into account the *temporal* aspect of the data by *NNs,* requires some architectural modifications in the *SNN* models by introducing *delay time* and *feedback loops* inside the neurons or in the network between layers and neurons in different manners and positions *(Tayarani-Bathaie et al., 2012*; *Abed et al., 2014; Xiaofeng, Chunshan, 2014); Vanini, 2014; Kuna, 2015; Shahbazi et al., 2016).* Therefore, the presence of *delay time* and *feedback loops* has a profound impact on the *learning capability* of the network, and on its *performance (Aggarwal, Song, 1997).*

There are multiple manners and classifications representing temporal information in *NNs (Yazdizadeh, Khorasani, 2002; Murugan, 2018)* used in the extensive applications for dynamic systems cited in literature. In literature we find a lot of sort of *NNs* belong to the *TNN* category such as the *RNNs* developed by *(Hopfield, 1984), Brain-State-in-a-Box* developed by *(Anderson et al., 1977);* the-*delay NN* developed by *(Lang et al., 1990), dynamic neural unit* (*DNU*) developed by *(Gupta, Rao, 1993).* One also finds other models such as of *(Jacquemin, 1994).*

(Isermann et al., 1997) divide *DNNs* into two groups: with *internal dynamics* and with *external dynamics*. *NNs* with *internal dynamics* are based on the extension of *SNNs* with internal memory. These extended networks show dynamic behavior in the sense that actual output data depend on actual and past input data. *(Abed et al., 2010; El-Shafie, Aminah, 2013; Beale, 2017)* have classified *TNNs* to *DTNNs* and *RNNs* respectively according to the time if it is treated by *delay time* in a *FFNNs*; or by *feedback* or *recurrence. (Yazdizadeh, Khorasani, 2002)* have classified *TNNs* to three categories: *TDNNs*, *RNNs* and *DNNs*. Indeed, there is a great ambiguity between *DNNs* and *TNNs*. The main representation of time is given by *(Chappelier, Grumbach, 1996)* according to the time where is treated, *externally* by *delay time* of the network, or *internally* by *recurrence* or *dynamic nodes* as shown *Figure IV.7 (Tayarani-Bathaie et al., 2012; Abed et al., 2014; Kuna, 2015). First*, the time is inserted *externally* as delays at inputs to the *NNs* to memorize data for certain duration. So, this technique, called *spatial presentation of time* according to *(Elman, 1990)*, has the advantage to use the architectures of the *SNNs* to process time. The *NNs* in this case are named *Time Delay Neural Networks (TDNNs) (Kim, 1998; Mohammadi et al., 2010). Second*, the *time* is treated *internally* in the *NNs*, where the name *internal representation* is derived according to *(Chappelier, Grumbach, 1996). The in this case are usually named, (Elman, 1990).* In this *internal presentation*, the time can be treated by two manners: (*a*) *implicitly* by using *feedback loops* (*recurrence*) of connections as in the case of *RNN;* or (*b*) *explicitly* by

using *dynamic neurons* in the case of *Dynamic Neural Networks* (*DNNs*). The structure of a simple *DNN* is similar to an *MLP*, with the difference that instead of conventional *static neurons*, *dynamic neurons* viewed previously have been used *(Yazdizadeh, Khorasani, 2002).* In both cases, *implicit* or *explicit*, the network has the capacity to memorize information. Furthermore, a combination can be doing between the different types of *TNNs*, particularly the *TDNNs* and *RNNs* which gives the existence to the *Time Delay Recurrent Neural Network (TRNNs) (Figure IV.7).*

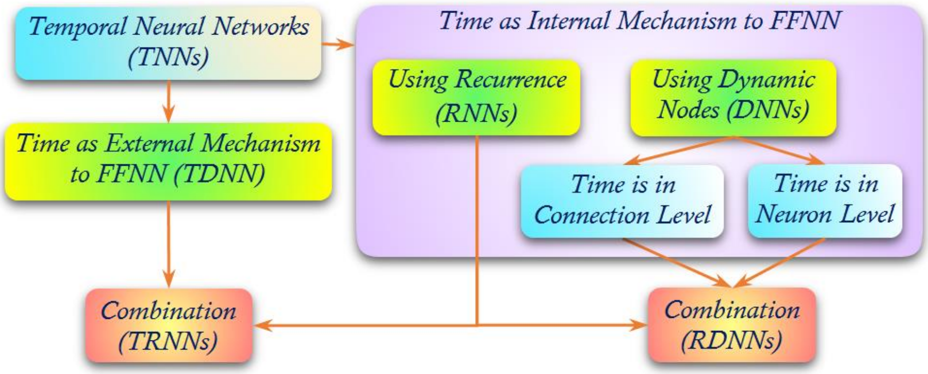


Figure IV.7 - Time representation in NNs.

IV.2.3.1 - Time Delay networks

One of the first architectures of *TDNN* called also *Tapped Delay Neural Network* has been introduced by *(Sejnowski, Rosenberg, 1986)* for text-to-speech conversion, then *(Waibel et al., 1989)* used this structure for speech recognition. The *TDNN* is straight forward *TNNs* which is simply consist of two components: A memory structure realized by *time delay* which hold on the relevant past information by introducing delayed inputs and outputs that are then fed to conventional *MLP (Abed et al., 2010)* which uses the memory to predict future occasions *(Tatem et al., 2002; Abed et al., 2010).* Depending on the choice of the linear filters the following three different external dynamic approaches can be distinguished. *Nonlinear Models with Output Feedback, Nonlinear Finite Impulse Response Model (NFIR)* and *Nonlinear Orthonormal Basis Function Model (NOBF).* For more details with regard to mathematical development and learning algorithm, readers are referred to *(Haykin, 2008).* The general *TDNNs* architecture is shown in *Figure IV.8 (Tatem et al., 2002; Haykin, 2009; Abed et al., 2014).*

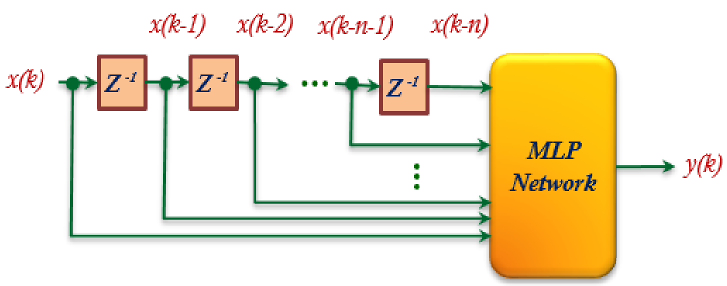


Figure IV.8 - TDNN architecture.

Another type of *TDNN* is *NETtalk (Tatem et al., 2002; Abed et al., 2014)* and *Time Delay Radial Basis Function* (*TDRBF*) with the same *spatial* representation of the time has been used for the same application by *(Berthold, 1994).* This type of network combines features from the spatial representation of time of the *MLP* and the *RBF networks*. His major advantage compare to the *TDNN* is the *simplicity* and flexibility of the training process, and the reduce number of parameters to adjust the training time *(Berthold, 1994).* Furthermore, it is envisaged that *TDNN*, in addition to better representation of biological neural systems, offer better computational capabilities compared to their static counterparts. The major inconvenience of these *TDNN* algorithms is due to the spatial representation of the time, *i.e.,* the existence of an external interface with the environment to delay and store data. The second disadvantage is the use of a temporal window that imposes a limit of the sequence length. *(Narendra, Parthasarathy, 1990)* have applied this type of neural structure for system identification and control of *NL* dynamical systems.

IV.2.3.2 - Time as internal mechanism

A - Recurrent Networks

RNNs *(Su et al., 1998),* are *special type* of *TNNs* *(Ngaopitakkul et al., 2011)* which are widely applied today owing to its effectiveness to solve almost all types of problem and has been investigated in *(Seker et al., 2003; Ngaopitakkul et al., 2011). RNNs* are equipped with one or more *feedback* connections that can be of *local* nature called also *self-feedback* where output of neuron is fed back to its own input), or *global* nature *(Marques et al., 2005; Menezes, Barret, 2006)* where output of neuron loop are fed back to neurons of the layer or to the preceding layers. So, the feedback can be between the neurons of a layer, and/or between the layers of the network. Therefore, in *RNNs* all possible connections between neurons are allowed *(Sinha et al., 2000; Witczak, 2007)* which implies that signals can flow in both forward and backward directions *(Marques et al., 2005).* Because of feedback paths from their outputs to the inputs, the response of *RNNs* is recursive *(Sinha et al., 2000)* which in turn increases its performance and learning abilities *(Gaya et al., 2014)* and *RNNs* becomes a *NL* dynamic system which changes continuously until it reaches a state of equilibrium. By construction, *RNNs* have an intrinsic dynamic memory: the output of a *RNN* networks is a function of the current external input together with its previous inputs and outputs which are gradually quenched. The output is described by the following differential equations *(Sinha et al., 2000; Marques et al., 2005)* :

$$y(k) = f\{u(k),\, u(k\text{-}1),\, \ldots,\, u(k\text{-}m),\, y(k),\, y(k\text{-}1),\, \ldots,\, y(k\text{-}n)\,\} \tag{IV.2}$$

Therefore, *RNN* is great for sequential data because each neuron acts as an internal memory to store information of previous input.

Different networks were built based on the recurrent network structure *(Karray, De Silva, 2004).* Generally, there are different kinds of recurrent networks depending on the way in which the feedback is. *RNN* can be classified as *Simple Recurrent Networks* or *locally recurrent globally feedforward* (*LRGF*)*; Partially Recurrent Networks;* and *Fully RNNs* *(Isermann et al., 1997).* Two kinds of the recurrent networks are well known, one of them is *Jordan*'s *network* and another one is *Elman*'s *network* *(Pasand, Malik, 1999).*

Elman's RNNs *(Elman, 1990, Racoceanu, 2003; Kuna, 2015)* *(Figure IV.9)* in which feed-back connections are from the outputs of neurons in hidden layer to the input layer neurons and *Jordan*'s *(Figure IV.10)* *(Racoceanu, 2003)* from outputs of the neural net to the inputs of the *NNs* *(Pasand, Malik, 1999; Seker et al., 2003).*
Elman's RNNs is a powerful network to extract the informative feature related to the dynamic system in its hidden layer. This property provides very important advantage, especially, in real time applications to follow the dynamical change in the considered system. On other side, *Elman network* has the unique time series prediction capability because of its memory nodes as well as local recurrent connections *(Gao et al., 2000).*

Other types of *RNNs* can be found in the literature like *Moakes (Racoceanu, 2003), Mak (Racoceanu, 2003), Miyoshi (Racoceanu, 2003), Recurrent RBF (Racoceanu, 2003), Dynamic General NN (Racoceanu, 2003; Racoceanu, 2003), Hopfield (Aggarwal, Song, 1998; Tatem et al., 2002; Racoceanu, 2003), Boltzmann machine, (Aggarwal, Song, 1998; Jalali et al., 2013), hierarchical RNN (Du et al., 2015), RNN with regularizations (Zhu et al., 2016)*, *differential RNN (Veeriah et al., 2015)* and *part-aware Long Short-Term Memory* (*LSTM*) *(Shahroudy et al., 2016)*. For other types of *RNNs* refer to *(Aggarwal, Song, 1998; Chiang et al., 2004a; Katte, 2018).* A comparison between major *RNN* architectures and some of the major advances in *RNNs* through time are provided in *(Salehinejad et al., 2018).*

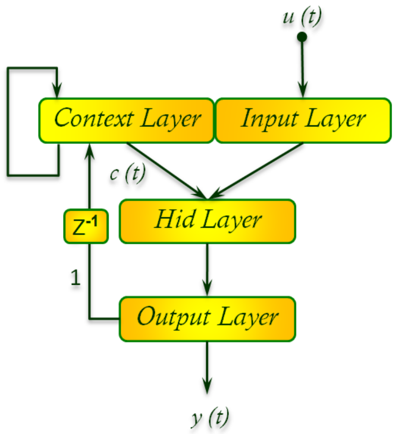


Figure IV.9 - Architecture d'Elman.

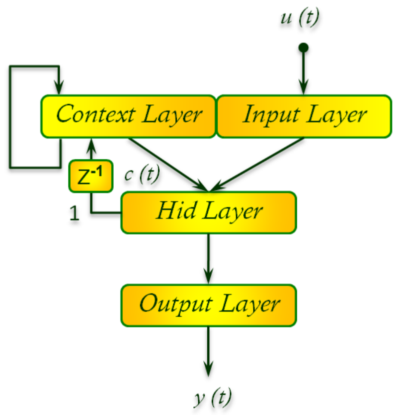


Figure IV.10 - Architecture de Jordan.

It was shown analytically that the *RNN* proposed by *(Funahashi, Nakamura, 1993)* is capable of identifying any nonlinear dynamic system provided that the initial states of the network are chosen appropriately with respect to the initial conditions of the system. Furthermore, *RNNs* architectures are naturally suitable for the sequence classification, where each input sequence is assigned with a single class *(Wang, Wang, 2017). RNNs* are particularly appropriate for system *modeling*, *control* and *filtering* applications *(Sinha et al., 2000).* Although for identification purposes this technique has not been as popular as the *TDNN* due to inherent stability complications, nevertheless this problem has been investigated by *(Funahashi, Nakamura, 1993).* Feedback allows the *RNNs* to acquire state representations, making them appropriate devices for different dynamic applications such as: prediction or modeling *NL* systems, control of industrial installations, processing of temporal signals and filtering *(Haykin, 2008; Sinha et al., 2000).* The *RNNs prediction* approach learns the model of the system from the external input information and the system itself. The *RNNs* inherit the mapping capability of *FFNN*s and, at the same time, capture the dynamic features of load information *(Huang et al., 2007).* Recently, *RNNs* have recently received a great deal of attention due to their capabilities in *modeling NL* dynamic systems *(Tayarani-Bathaie et al., 2012).* They have been developed as a modeling technique for *predicting* and showed high accurate *prediction* when compared with conventional creep models *(El-Shafie et al., 2009). RNNs* are capable to represent arbitrary *NL* dynamical mappings *(Narendra, Parthasarathy, 1990),* such as those commonly found in *NL* time series *prediction* tasks. Therefore, these networks are important because many of the systems that we wish to *model* in the real world are *NL* dynamical systems *(Sinha et al., 2000).* This is true, for example, in controls area in which we wish to *model* the forward or inverse dynamics of systems such as airplanes, rockets, spacecraft and robots *(Haykin, 2008; Gupta, Rao, 1994).*

IV.2.3.3 - Combination

When both adaptive time delays and recurrences were used, It is more useful to improve performance *(Kim, 1998; Mandic, Chambers, 2001).* The combination of a typical *MLP* network with adaptive time delay units and feedback for processing temporal information of inputs sequences is known as *TDRNNs (Su et al., 1998; Jain et al., 2015).* This *TDRNN* will be well applicable for temporally continuous domain, such as speech recognition, language processing, temporal signal identification and *FM*.

(Kim, 1998) has presented a *TDRNN* for temporal correlations and prediction. The simulation results have shown that the *TDRNN* well learn temporal correlations between current data and past events by using dynamic time delays and recurrences and the best performance is attained.

The *NL Auto-Regressive with eXogenous inputs* (*NARX*) is one class of *TDRNN* models. The *NARX network* was developed based on *AutoRegressive with Exogenous Input* (*ARX*) which is commonly used in time-series modeling *(El-Shafie, Aminah, 2013; Liu et al., 2010)*. So, *NARX* is the extension of an *ARX* model *(Kannan, Rathinam, 2012)*. In this study *NARX NN* is used and it represents feedback dynamic *TDR NN* where the outputs in time series depends on both, current inputs and previous outputs *(Banjanović et al, 2016)*.
Figure IV.11 shows the topology of *NARX* network *(Menezes, Barret, 2006; Huang et al., 2007; El-Shafie, Aminah, 2013)* in which two types of *NARX networks* architecture are presented as proposed in the literature *(Menezes, Barreto, 2008)*. They are *parallel* (*P*) and *series-parallel* (*SP*) architectures *(Ruslanet al., 2014)*.

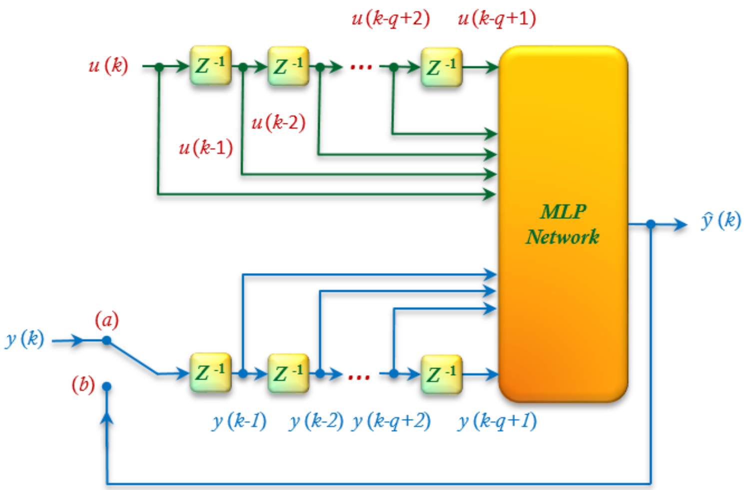


Figure IV.11 - Serial/parallel architecture for NARX model (Shahbazi et al., 2016).

(Talebi et al., 2014) suggested *dynamic recurrent NNs* (*DRNNs*) for *FDe* system by using a comprehensive dynamic model which contains both mechanical and electrical components of the wind energy conversion systems.

IV.2.4 - Training

NNs are *data-driven self-adaptive* methods in that they can *adjust themselves* which involves tuning the weights associated to connections by learning from a set of existing input/output training data. These *data* can either be *collected* from the *process itself* or from a *simulation model*. The *second possibility* is of special interest for *collecting data* of the *different faulty* situations in order to *test* the *residual generator*, since generally; those kinds of data are not available at the real process. Before the beginning of training, the initial weights and node threshold are chosen randomly. The goal behind weights and biases adjustment by an appropriate *training* (using a learning) of a *NNs* is to minimize the difference between output of the network and desired output represented as *Mean Square Error* (*MSE*), shall reach the minimum probable value.

$$MSE = \frac{1}{2}\sum_{j=1}^{N}(\, target_i - output_i)^{2} \qquad \text{(IV.3)}$$

where $target_i$ denotes desired output (provided by teacher) and $output_i$ is network's prediction of the output for the corresponding *input*, both (*i.e. input* and *output*) of size *N* and order *i*. For learning operation of the *NN*, the training data are usually divided into three subsets, *training*, *validation* and *testing*. Moreover, the number of training samples should be large enough to satisfy the *Vapnik–Chervonenkis* requirements. The most important task in the *validation* phase is to check the performance of the network to determine the epoch at which training should be stopped to avoid *over-fitting* *(Jalali et al., 2013).*

During the training phase, the training data set is presented repeatedly to the network followed by adjustment of the weights according to the training algorithm until the output signal converges to the desired one. The *training* is periodically interrupted for *validation* set presentation, in order to *evaluate* the network *generalization.* The *test* set is applied to *evaluate* the *NN performance*. Finally, once a network has been structured for a particular application, it is ready for training.

There are three major learning paradigms; *supervised*, *unsupervised* and *reinforcement learning* *(Da Siva et al., 2017).* Each learning paradigm has many training algorithms. Various types of *learning algorithms* have been proposed such as *back-propagation*, *gradient descent, MSE, Livenberg-Marquardt*, *etc*. The extension of back-propagation to dynamic applications is known as *extended dynamic back-propagation algorithm*. The three first ones are widely used for effective learning in *feed forward networks*. (For more details about *NN training methods* refer to *(Bishop, 2007).* Basically, the purpose of every algorithm is to estimate the local error at each neuron and systematically update the network weights. Their *convergence* is a crucial criterion for *NN*s to be useful in different applications *(Arik, 2005; Liang, Cao, 2004).* Therefore, considerable effort has gone into developing techniques for accelerating this convergence. Among *NN*s *learning algorithms, back-propagation*, or *backward propagation of errors*, "*error back propagation*" *propagation* is the most commonly used, supervised learning (training) algorithm for adapting connection weights because of its capabilities for solving complex *NL* problems. However, *error back propagation* algorithm is *slow* and *inefficient* therefore, many enhancements have been introduced. By using *error back propagation* algorithm, connecting weights are tuned on the basis of a *Gradient Descent Method* to minimize square error for all training input–output pairs (the difference between the desired output values and the output signals produced by the network).

IV.2.5 - Features and Performance

The main features that facilitate and attract the use of *NN*s are as follows: (*a*) The *highly NL characteristics* *(Kourd et al., 2013; Mandal, 2015)* of *NNs* make them suitable for dealing with *NL* and *complex* dynamic systems *(Tayarani-Bathaie et al., 2012*; *Khireddine, 2014);* (*b*) *NN* is considered as a veritable massively *parallel distributed processor* *(Aggarwal, Song, 1997)* which can compute simultaneously several similar and independent operations. This feature allows *NNs* to perform different tasks more efficiently with high speed of operation and processing when implemented in hardware(*c*) Furthermore, *NN*s have the ability to *self-learn* through examples *(Matic et al., 2010a; Kourd et al., 2013; Srivastava et al., 2014)* and to *generalize* the learned information (knowledge) which are extremely interesting properties to *adapt itself* *(Aggarwal, Song, 1997)* by modify its internal structure during use to unlearned and arbitrarily data, and in response to changing environmental conditions *(Sorsa, Koivo, 1993; Matic et al., 2010a).* (*d*) Moreover, The generalization capability of *NNs* enables *NNs* to have a great promise for use and to make intelligent decisions in environments even the incoming *data* are *distorted, noisy, sparse, incomplete, uncertain, corrupted* or *erroneous* *(Palade et al., 2002; Kourd et al., 2013; Srivastava et al., 2014).* Finally, *NN*s have capabilities to deal with highly *nonlinearity*, complexity, uncertainty, noisy or corrupted data. Furthermore, every type of *NNs* has its advantages and its drawbacks with a size vary from one neuronal architecture to other and the relevance of one type over the others is strongly related to the considered application *(Koivo, 1994).* However, they are a promising *alternative* to various conventional *methods* because they have potential *advantages* over them *(Zhang, 2000).*

IV.2.6 - General use of NNs

Due to their high potential dynamics, *NNs* have been emerged as a viable, power and effective tool for many researchers to solve challenging problems for a variety of applications in different field of engineering and science *(Maria et al., 2008; Psillakis, 2010), combinatorial optimization (Min et al., 2010), information prediction (Yao, Xu, 2006) and other fields*. These application can be dynamic or static according to the nature of the used *NNs. (Chiradeja, Ngaopitakkul, 2009; Changjun et al., 2010)* provided a good overview of potential and successfully applications of *NNs*. These applications, particularly of *FM,* are generally based, as is shown on *Figure IV.12,* on two main categories *(Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c; Zhou et al., 2003; Korbicz et al., 2004; Lipnickas, 2006) :* (*a*) the *approximation (Tayarani-Bathaie et al., 2012; Khireddine, 2014)* including *estimation (Yu et al., 1999)* or *prediction (Baughman, Liu, 1995), identification (Zemouri, 2003; Majetic et al., 2014)* and *modeling (Tayarani-Bathaie et al., 2012*; *Khireddine, 2014)* of the *dynamic* of *complex NL* systems *(Liang, El Maraghy, 1993);* (*b*) and the *classification (Venkatasubramanian, Chan, 1989)* including *PR* function from noisy complex data *(Uppal et al., 2006)* with great flexibility and capability *(Tayarani-Bathaie et al., 2012; Khireddine, 2014).*

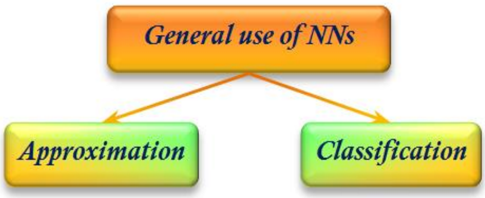


Figure IV.12 – General classification of NN applications.

IV.2.6.1 - Approximation

Approximating a *continuous function* is an underlying relationship between input and output *(Khireddine, 2014).* It is a real mapping (link) of set of input to output data variables and parameters of dynamic system *(Tayarani-Bathaie et al., 2012; Khireddine, 2014).* The approximation of one or more process variables is made with a set of other related variables *(Tatem et al., 2002).* The *learning* and *generalization* features permit to *NNs* to approximate the relationship between the input and the output *(Khireddine, 2014)* by using unseen input data. *NN*s have been shown to possess an inherent ability in *approximating* both the *linearity* and highly *non-linearity* of continuous complex relationship or function representing the behavior of dynamic systems and process *(Haykin, 2009; Mohammadi et al., 2010).* Recently, they have been shown the ability to give continuously excellent and proficient *approximation (Wei, Chaudhary, 2015),* massively and fast up to any desired level of *accuracy (Haider, Zeng, 2009; Mandal, 2015)* even for large data sets *(Ratsko et al., 2002; Tatem et al., 2002).* Therefore, *NNs* are known as *universal approximates (Gururajan et al., 2013). Approximation capabilities* of *NNs* are widely publicized and for a detailed review of the issue one may refer to *(Basheer, Hajmeer, 2000; Tikk et al., 2003).* The *MLP* and *RBF networks* are widely used and gave good results in *approximation (Li et al., 2012; Heger, 2015).* Particularly, with at least one hidden and large enough number of hid neurons, these networks are the most commonly used network type for data *approximation* once enough training is provided. Therefore, both networks are proved to be *universal approximators* of any static *NL* mapping *(Hornik et al., 1989).* However, *SNN* has become the most *used* form of *NN* in representing *NL* processes, this network is *not dynamic* in nature and does not take into consideration the delay time that affect the dynamics of the system.

The nature of *NN* makes it possible to model systems without *using physical expressions* when only operating samples (data) of system inputs and outputs are available *(Guo, Uhrig, 1992a).* Due to its *approximation (Palmé et al., 2011; Kuna, 2015)* and *prediction* capabilities, *NN*s are able of performing *modeling* the behavior of *highly*

complex dynamic NL systems and providing an excellent black box tool of *modeling*, by provide the necessary tools for establishing mappings between system readings and its state *(Mohammadi et al., 2010; Majetic et al., 2014; Mandal, 2015). NNs* are recommended to be used for *modeling* multi-output process system based on the operating measurement (data) information. When *NN is* used to model a system, the input layer of *NNs* corresponds to the input signals of modeling system, and the output layer has one or several signals to be *predicted* or *estimated (Palade et al., 2002; Zhou et al., 2003; Srivastava et al., 2014). NN*s learn from given data and capture the underlying (unknown) functional relationships. Indeed, many of the systems that we wish to model in the real world are complex and *NL dynamical,* in their nature *(Sinha et al., 2000)*
such as nuclear and chemical reactors, airplanes, rockets, spacecraft and robots. The distinguishing features make *NNs* the most powerful computer techniques and suitable *modeling tools* of the process dynamics of the industrial plant in recent years as an *excellent flexible alternative (Jayawardena et al., 2000; Patra et al., 2010)* with good capabilities *(Kourd et al., 2013; Toma et al., 2013; Wang et al., 2014)* to the conventional *MM-based* approach describing the process *under normal operation*. *NNs* online training capabilities can *reduce modeling errors* (and therefore reduce the *FAl* rate) in comparison to other *time-invariant mathematical methods*. The most commonly *used network architectures* for process *modeling* include the *MLP*, the *RBF* and the *AANNs.* However, the *SNNs* with no *temporal aspect in structure, cannot model* accurately this kind of systems. Advanced network architectures such as *DNNs* including *recurrent*, *time delay networks* are important and particularly appropriate for dynamic system *modeling* applications *(Sinha et al., 2000; Biyanto et al., 2007). DNNs* are appeared to be very promising approaches and more versatile. They provide the capability to learn the *dynamics* of *complicated NL systems* and provide better understanding which conventional *SNNs* cannot do *(Xuhong, Yigang, 2005).* For this reason, these networks (*i.e., DNNs*) have recently received a great deal of attention for use in *NP*s due to their capabilities in *modeling* of slower dynamic behavior which is inherent to *reactors.*

Obviously, the *NN* is a powerful tool for *NL prediction* of states and parameters *(Abed et al., 2010; Wei, Chaudhary, 2015).* The *success* of *NN* architecture in *describing* the *dynamics* of a system and *predicting* the future behavior *depends* largely on the *choice* of its *type* and *structure (Ramasamy, 2007; Abed et al., 2010; Wei, Chaudhary, 2015). (Kaminski et al., 2011; Majetic et al., 2014; Wei, Chaudhary, 2015). (Baughman, Liu, 1995)* have mentioned that networks with *one hidden layer* show their ability to *estimate* a value with a sufficient degree of freedom. Unlike *SNNs*, *DNN*s contain delay times and feedbacks. This aspect gives them more ability to predict dynamic systems. Among numerous of possible of *NNs* configurations, the *RNNs* are known to be particularly effective in learning temporal patterns, to be superior in performing modeling technique *predictions (Huang et al., 2007)* and showed high accuracy when compared with conventional other models *(El-Shafie et al., 2009).* Indeed, *RNNs* are able to represent arbitrary *NL* dynamical mappings *(Narendra, Parthasarathy, 1990),* such as those commonly found in *NL* time series *prediction* tasks. *RNN* model extracts the true dynamics from the noisy data, and ideally the prediction error will be only the measurement noise. Two *NNs* architecture has been considered: a *TDNN* for response prediction and a *RNN* for identification. Comparisons between the *TDNN* and *RNN* have been presented *(Marques et al., 2005).*

The *RBF* and *MLP* are widely used and give good results in process *identification (Racoceanu, 2003; Mamar, 2008).* Due to their local and global generalization capabilities, *RBF networks* have been extensively used as the basic structure of *NNs* for *NL system identification (Fabbri, Kadirkamanathan, 1996).* Within the different architectures of *NNs*, an important class is given by the *RBF networks (Eberhart et al., 1996).* A class of this *network*, which has shown to be particularly suitable for on-line system *identification* problems *(Sanner, Slotine, 1992),* is known as *Resource Allocating Networks* (*RAN*).

IV.2.6.2 - Classification

Moreover, of the *approximation* application, *NNs* demonstrated the ability to be robust and speedy approach, and provide a *powerful capacity* and *optimal solution* for performing *classifiers (Chen et al., 2003; Evsukoff, Gentil, 2005)* in different domains such as in *FM (Sorsa, Koivo, 1993)* including *PR* problems *(Chen et al., 2003).* Classification methods get all their information from the data through training. The *classification* network needs to be trained to create decision surfaces which minimize the classification error. The classes should be equally big and a batch training method employed, *i.e.*, the network weights should be updated after seeing all data patterns. *MSE* Traditional *classification methods* are normally *parametric*, which means that the *discriminant function* separating different classes has a well-defined *mathematical form* (*e.g., Gaussian)* which depends on a set of parameters, *mean* and *variance*. However, *NNs* are considered to be *semi-parametric*, which means that the data is used to create the *discriminant functions*. This form of input-output *mapping* is well appropriate for *PR (Chen et al., 2003)* applications where both the input and output represent *spatial patterns* that are time independent *(Sinha et al., 2000).* Like other *PR* techniques, *NNs* act on data by detecting some form of underlying organization not explicitly given or even known by human experts *(Aggarwal, Song, 1997).*

Many types of *NN*s can be used for *classification* purposes *(Zhang, 2000). Four* principal types of *neural classifiers* have been usually applied: the *MLP, RBF*, *self-organizing Kohonen's network* and *hybrid NN*. The *RBF* and *MLP* give good fairly *classification (Mamar, 2008)* and *PR (Li et al., 2012; Heger, 2015).* With both *MLP* and *RBF* networks architectures it is possible to achieve better performance than other techniques such as the *nearest-neighbor classifier (Sorsa, Koivo, 1993)* and *SVMS (Mamar, 2008).* The *MLP network* is used in many *classifications (Becraft, Lee, 1993; Zhang, 2000; Patel, Yalamalle, 2014* and *mapping* problems due to their *good results*. They can reliably *classify* the training patterns and allow obtaining satisfactory performance *(Simani, Fantuzzi, 2000). MLP* with one hidden layer, a *NL* transfer function in the hidden layer, and sufficient number of neurons and training data is able to create any arbitrary discriminant function *(Palmé et al., 2011).* On other side, the result showed that *RBF network* has very high learning convergence speed and better *classifying* performance *(Yi, 2010). RBFs network* are not as easy to use as the *MLPs* but *RBFs* may perform classification better and showed severe limits when they are trained with *noisy* data *(Simani, Fantuzzi, 2000)* as long as their parameters are carefully determined. The *Kohonen's feature map* is *unsupervised* trained, is not always able to *classify* even the data training correctly. However, its ability to *classify* the measurement data autonomously is useful and very interesting, particularly when real industrial processes are considered *(Sorsa et al., 1992).* In practice, the definition of different fault situations is a big problem and therefore *unsupervised* trained *NNs* provide a promising method for *FDD*. In *(Koivo, 1994),* three types of *NNs* were tested: the *MLP*, the *RBF* and the *Kohonen's card*. On the other hand, the *Kohonen's* network is not as good as the *MLP* and *RBF*, but its self-adaptation capabilities (*unsupervised learning*) are very much appreciated.

(Kannan, Rathinam, 2012) used *six NN*s for the *classification* of *high impedance faults (HIF),* namely *BP network*, *cascade correlation network*, *RBF*, *learning vector quantization*, *NARX network* and *adaboost classifier.* Other references of the use of *NNs* in the classification can be found in *(Liang et al., 2001).*

IV.3 - Monitoring by NNs

NN-based model has been used in the *FM* for several decades. In late 80*s (Venkatasubramanian, Chan, 1989)* proposed a *NN*-based methodology for process *FM*. In recent years, a great deal of attention has been paid to the development of a large variety of methods for different *applications* for *real-time monitoring* and control issues. One of the popular among these methods, that based on *AI* and mostly *NNs* are widely researched *(Calado et al., 2001; Korbicz et al., 2004; Gang et al., 2013).* Reviewing the application of *Computational Intelligence (CI),* methods to *FDD* were the subject of many researches *(Patton et al., 2000).* The application of *NNs* for *FM* has generated considerable research. Usually in this field, *NNs* can be classified along two dimensions *(Venkatasubramanian et al., 2003c),* the *architecture* of the network and the *learning strategy.*

The *NN*s capabilities, cited above, permit the *NN*s to have been successfully applied to *FM (Palade et al., 2002).* Various studies were presented about *CM*, *FDe*, and *FDi* using *NNs (Simsir et al., 2016)* and already shown good performance *(Nabeshima et al., 1998). NNs* have been used in various applications, including *FDe* and *FDi (Mrugalski, 2013; Rajendran et al., 2013; Wang et al., 2014)* and have been successfully applied in different domains cited above. But even more *NNs* have become a sort of ideal and powerful tool for *FM (Aminian, Aminian, 2002; Ab. Rahman, 2010)* of *NL* dynamic systems using the *system's generated data*.

Most of the *NNs applications* for *FM* use the *FFNN* structure with some variation of the *BP* training algorithm *(Furukawa et al., 1995; Jeong et al., 1996; Reifman et al., 1996).* Among other types of network structures proposed for *FM* are the *Kohonen self-organizing network (Haykin, 2009), the perceptron-like network (Ragheb, Campos, 1990),* the *temporal network (Uluyol, Ragheb, 1993),* the *probabilistic network (Bartal et al., 1995),* the *Boltzman machine (Marseguerra, Zio, 1994),* and *RBF network (Renders et al., 1995).*

*NN*s are *used* in *two ways* regarding process *FDD in power plants*. The *first* use is as *residual generator (Ruz-Hernandez et al., 2005)* in the sense that *NN*s are used to capture *NOCs* of the system. The *second* application is as fault *isolator* or *classification* technique *(Leger et al., 1998; Simani, Fantuzzi, 2000).*

NNs can be used for *FDD* in *three* different *manners.* (*a*) Instead of performing the two steps of *FM,* one-step *monitoring* might also be possible *(Köppen-Seliger, Frank, 1995)* which means *FDe* and *FDi* are made together with the same *NN.* So, the ability to combine *detection*, *isolation*, and *accommodation* in one step is the key *advantage* of *NN supervision scheme*. (*b*) In *both-steps* of *FM (Chen, Patton, 1999; Mamar, 2008; Ab. Rahman, 2010)* which means *NN* is used in *FDe* in conjunction with an additional *NN* for *FDi (Yu et al., 1999; Chen et al., 2003).* (*c*) Only *one time*, in *FDe* or in *FDi* and the remain stage is mad by another approach *(Mamar, 2008; Ab. Rahman, 2010; Srivastava et al., 2014).* Example, a *NN* used as model-based *FDe* and *FDi* is made by another technique *(Köppen-Seliger, Frank, 1995).* When *NN is* used in *FDi* to perform the classification task for residual evaluation and therefore *FIso (Köppen-Seliger, Frank, 1995),* all *residuals* have to exist which can be generated *analytically* by using *MM* methods *(Yu et al., 1999; Chen et al., 2003).*
In the case (*a*), the *NNs* can be used to generate *residuals* and isolate faults *(Chen, Patton, 1999). FFNNs* have been used primarily as a transient *classification* tool to detect and *identify* a set of pre-specified component failures *(Xing, Okrent, 1994; Jeong et al., 1996; Reifman et al., 1996).* As example in the case (*b*), *(Bae et al., 2006)* have constructed *FM* of *NPP* by using two-steps *NNs*; one is to *detect* the *failure* severity and the other is to *classify* the *failure* type. *(Zhou et al., 2003)* developed two *NNs* for *NPP monitoring*. *MLP* is used as residual generator to *detect* the symptom of anomalies and *RBF* to *identify* the abnormal events. *(Yu et al., 1999)* used successfully *two RBF* networks for sensor *FDIso* in a *chemical reactor process*; *one* is used as model to for *generate residual* for *FDe* and *another* as *classifier for FIso.* In *(Dang, 2007),* the analysis of the data obtained is done using two stage *NN*, where, the *first* stage is used for *estimation* of *PC* and the *second* stage for *classification.*
Furthermore, for the case (*c*), other studies used a hybrid *FDI* scheme in which observers are used for residual generation and *NNs* for *FId (Simani, Fantuzzi, 2000; Simani, 2005).* In some cases of the hybrid *FDI* scheme use, the *FDe* tasks were performed through the use of a bank of dynamic observers, particularly a *bank* of *KFs* and *EKF* when the measurement noises are not negligible *(Srivastava et al., 2014),* and *NNs* for *FId*. *(Adouni, 2013)* presented a scheme for *FDI* of *sensors* and *actuator* fault of an induction machine. The generation of *residual* for the *FDe* phase is based on *NN* and the *residual* analysis is made with *FL*. *(Ding et al., 2002)* used a hybrid method involving a combination of *MM* with *NN* and arrived at a faster computing algorithm for the study of *HEs*.
NNs can handle *NL* and undetermined processes because no process model is needed but *NNs* learn the *FDi* by means of the information of the training data *(Sorsa, Koivo, 1993).*

IV.3.1 - Fault Detection

The *detection* function is *necessary* since it is placed at advanced place in monitoring procedure. In the ideal situation, if the value of a *neuron* in the output layer of the network is equal to one, then the fault represented by that particular neuron is considered to be present. Conversely, if the output of a neuron in the output layer is equal to zero, the fault is judged to be absent.
Moreover, of the *approximation* application as *modeling processes* with strong *non-linearity* and robustness for *FDe* *(Evsukoff, Gentil, 2005),*

Several *FDe* methods have been introduced including *geometric (Edwards et al., 2000; Guo et al., 2008)* and adaptive *estimation methods (Zhang et al., 2002; Jiang, Chowdhury, 2005)* for *NL* continuous-time systems while others *(Tan et al., 2008; Talebi et al., 2009)* have used *sliding mode observers* and *fuzzy-based observers (Yan, Edwards, 2008).* Advanced methods of *FDe* are mainly based on process *modeling* and on mathematical *SP* to *generate* fault *symptoms (Heredia et al, 2008).* A survey of *FDe* schemes for robot *(Lopez-Toribio, Patton, 1999), hydraulic systems*, *flight control etc*., are given *(Dixon et al., 2000).*
Reactors have *complex NL dynamics* such that *classical analytical model* and other *FDe methods* have several drawbacks so, they are too heavy to use in practice and too expensive to get.
It should be noted, however, that in cases where only poor or imprecise analytical models are available, the model-based FDI approach still problematical especially when there is no, or not sufficiently accurate mathematical and physical expressions acknowledge. In such cases, the support by data-based methods may be unavoidable. Hence, an approach based on physics is still far from being realized and researchers have therefore focused attention on the use of *DDT*s in the recent years.

With the development of *AI*, many techniques and systems based on *intelligent* and *learning-based strategies (Patton et al., 2000),* have been applied in *FDe* with the purpose to assist the *NPPs operators* to correctly interpret the fault data, including *ESs*, *NN (Rovithakis et al., 2004; Samanta, 2004), FL (Goode, Chow 1995) GAs (Raymer et al., 2000; Rovithakis et al., 2004)* and combination of them such as *fuzzy NN*. Many *methods driven* by *data* have been proposed to model *NL* processes *(Nelles, 2001).* The non-limitation on *LS*s is why the use of *NNs* with *online learning* capabilities is steadily growing in the *FDe field (Isermann, Ballé, 1997).*
However, in *comparison*, a *KF* provides better *noise filtering* and *excellent dynamic estimates* of the outputs of *LS*. For *NL systems*, the *EKF* can be used, but it imposes a much greater *computational burden* because of the complexities involved with *representing* a *NL system* with a family of piecewise *linear models*.
So, *NN* have been as a good mathematical tool for modeling the process of the industrial plant for model-based abnormal detection. *(Marcu, Mirea, 1997)* investigates *SNNs* and *DNNs* that are used to approximate the *NL* dynamic models of a plant, for both normal behavior and components' faults. In *(Gupta et al., 2015)* three different types of *NNs* (*RBF* network, perceptron NN and *MLP*) are used for generate a fault model for *FDe* of *RC-Coupled amplifier circuit* and show their high efficiency. These *NNs* are based on slope fault feature extraction method.

The ability of *NN* to detect any process faults is based on their ability to learn from example and requiring little knowledge about the system structure *(Ab. Rahman, 2010).* Different *advantages* of using *NNs* instead of other *FDe* techniques are discussed in more detail in *(Han, Yang, 2006).*
Due to the capability of *NNs* with respect to noise, it is able to provide stable, highly sensitive and economic *FDe*.

IV.3.1.1 - Estimation and Modeling

Due to their proprieties (mentioned above) *NN* have been used as a *dynamical model* in *FDI* of the process of the industrial plant *(Song et al., 2010; (Zhou, Zeng, 2012). NNs modeling techniques* were suggested as viable solutions for monitoring issues in *NPP* as early as 1988 *(IAEA-TECDOC-542, 1988).* However, the *modeling* for *complex* and *NL* systems such as an *NPP* is a formidable task if many reasonable *approximations* and simplifications are not tolerated. The power ability of *NNs* to model give them a great *benefit* to the *NR monitoring*, apart from other numerous application areas *(Uhrig, 1991).*

For evaluating the performance of a network, some criterions can be used to observe the error between desired responses and calculated outputs. Among them, we find *MSE (Chiang et al., 2004a), Index of Agreement (IA), MeAE*, *MAE*, *Symmetric Mean Absolute Percentage Error (SMAPE) (Swanson et al., 2011), RMSE, Relative Mean Absolute Error* (*RMAE*) *(Chiang et al., 2004a), MAE* (%) *(Samy et al., 2010)* and *CC. MSE,* given by *Equation IV.3,* is able to observe deviations between experimental and calculated values of process variables.

The *IA (Willmott, 1981)* developed as a standardized measure of the degree of model prediction error and varies between 0 and 1. A value of 1 indicates a much perfect and 0 indicates no agreement at all. It is dimensionless statistics and its value should be evaluated based on the studied phenomenon, measurement accuracy and the used model. *IA* becomes intuitively *meaningful* after repeated use in a variety of problems. It is expressed in the following *equation* (*Equation IV.6*).

$$IA = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i' - \hat{y}_i')^2} \quad \text{(IV.4)}$$

where $y_i' = y_i - y_m$ and $\hat{y}_i' = \hat{y}_i - y_m$

The *MeAE* is given by *(Chiang et al., 2004a).*

$$MAE = \frac{\sum_{k=1}^{N}|(y_k - \hat{y}_i)|}{N} \quad \text{(IV.5)}$$

The *SMAPE* index is an average of the absolute percentage errors can be used for the evaluation of *NNs*. These errors are computed using a denominator representing the average of the forecast and observed values. SMAPE offers a well-designed range to judge the level of accuracy and should be influenced less by extreme values *(Swanson et al., 2011).* It is expressed in.

$$SMAPE = \frac{1}{n}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{(|y_i| - |\hat{y}_i|)/2} \times 100 \quad \text{(IV.6)}$$

The *Root Mean Square Error* (*RMSE*) is given by *(Chiang et al., 2004a)* :

$$RMSE = \sqrt{\tfrac{1}{n}\textstyle\sum_{i=1}^{N}(y_i - \hat{y}_i)} \quad \text{(IV.7)}$$

The *RMAE:*

$$RMAE = \frac{MAE}{\bar{y}} \quad \text{(IV.8)}$$

(El-Shafie, Aminah, 2013) gave the modified performance function which is defined by adding a term that consists of the mean of the sum of squares of the network weights and biases to the original MSE function as:

$$MSE_{reg} = \gamma\, MSE + (1-\gamma)\, MSW \quad \text{(IV.9)}$$

where γ is the performance ratio that takes values between 0 and 1 and MSW is computed as:

$$MSW = \frac{1}{M}\sum_{j=1}^{M} w_j^2 \qquad \text{(IV.10)}$$

where *M* is the number of weights used inside the network structure and w is the weight matrix of the network. The *CC* is a measure of the strength of the linear relationship between two variables. A *CC*'s value which is close to -1 or +1 indicates a strong correlation between the variables.

IV.3.1.2 - Residual Generation

Due to their proprieties (mentioned above) *NN* have been used as a *dynamical model* in *FDI* of the process of the industrial plant *(Mohammadi et al., 2010; Song et al., 2010; (Zhou, Zeng, 2012).* Furthermore, due to its modeling abilities and noise prevention, *NN* is considered as promising and even ideal tools for generating *residuals* from the measurement information independently of the nature of application and dynamic characteristics of the plant and dependent only on faults. They are able to *detect* any small process *faults* independent of the dynamic characteristics of the plant with high accuracy and earlier than the conventional approach by using only input-output data measurement of the system.
Furthermore, *on-line approximation* based schemes using *NNs* are considered as *NL adaptive observers (Hammouri et al., 2002)* which are used to detect changes in *NL system* behavior due to faults progression when the dynamics of these faults are unknown. *(Lin et al., 1996)* have proposed the use of *FFNNs* exclusively for *FDe*. *(Yu et al., 1999)* used the *RBF* network as model for the fault-*detection residual* generator.

Before applying the *NN* for *residual generation* for *FDe* then *evaluation* for *FDi* first, the network has to be *trained* for this task. For this purpose, a residual data base and a corresponding fault signature data base are needed. Therefore, an *input signal* and a corresponding *output signal data base* have to exist as illustrated by *Figure IV.13*.

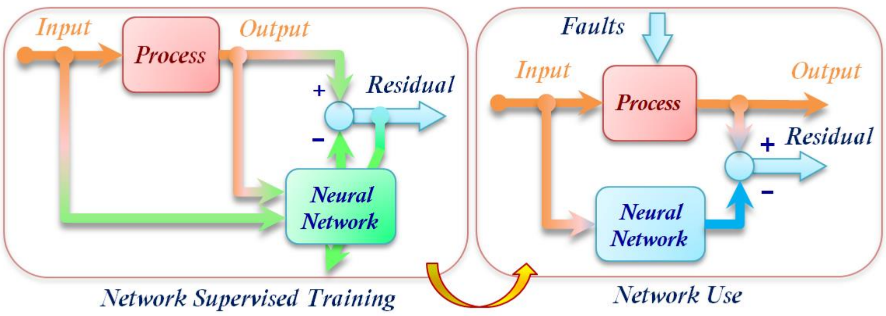


Figure IV.13 - Scheme for training and on-line application of NNs for residual generation (Köppen-Seliger, Frank, 1995).

The appropriate choice of the input space is one of the most difficult tasks when configuring the *NN*. One either needs to have enough process knowledge and then use a trial and error strategy or has to apply an optimization algorithm such as a *GA (Köppen-Seliger, Frank, 1995).* After the training is properly finished, the *NN* internal parameters allow to *NN* to be used for *residual* generation in real-time without need to prior qualitative *MM (Uhrig, 1991).*

(Nabeshima et al., 1998) used three-layered *AANN* as *modeling tool* for symptoms detection of small anomalies in real-time operation of *NPPs* in over the wide power range including start-up, shut-down and steady state operations. *(Nabeshima, 2005)* used the *AANN* to *model* the *reactor dynamics* for *CM* and *SeV* during power increasing and steady state operation in real-time of *multi-purpose reactor* (*RSG-GAS*) in *Indonesia*. The test results showed that this plant *monitoring* system is successful in detecting the symptoms of small anomalies in real-time over the wide power range. In *(Seker et al., 2003) RNN* and *FFNN* were able to *detect* the *very small anomaly*

induced towards the tail of the operation but the *RNN* has shown a better performance than the *FFNN* model during the simulation beyond the learning period. *(Talebi et al., 2014)* suggested *dynamic recurrent NNs* (*DRNNs*) for *FDe* system by using a comprehensive dynamic model which contains both mechanical and electrical components of the wind energy conversion systems.

IV.3.2 - Fault Diagnosis

To improve the performance of *FDi* system, *AI* techniques such as *FL (Lemos et al., 2013) NNs (Mahammed, Hiyama, 2011; Korbicz et al., 2004), GAs (Ziani et al., 2012)* and *SVM (Sugumaran, Ramachandran, 2011)* have been increasingly applied over conventional approaches. Among *AI, NNs* are a promising *alternative* to various *conventional* statistical *methods (Zhang, 2000).* More recently, the potential of *NNs* for *FDi* has been demonstrated *(Catelani, Fort, 2000; Shen et al., 2002)* because they have potential *advantages* over them. The general mapping capability of the *NN* enables to identify a fault easily *(Cheon et al., 1993). NNs* used for process *FDi* usually use measurements and process alarms as inputs, while the outputs represent particular fault types, or categories *(Becraft, Lee, 1993).*

In practice, there are usually a few measurement patterns for each fault situation and plenty of data corresponding to normal operation. In addition, in industrial applications it is not always possible to determine the causes of faults. Therefore, supervised learning cannot always be applied in a direct way and it is important to investigate both supervised and unsupervised learning alternatives for *NNs*. This issue has not been seriously discussed in the *FDi* literature. One possible way to approach problems where the causes of faults are difficult to determine is to classify the process measurements according to the way the process is run. Unsupervised trained networks can be used to find different ways of running the process *(Sorsa et al., 1992).* The *use* of *output neuron values* to *determine* fault *magnitudes* has been examined *(Watanabe et al., 1989).* Moreover, fault *size* estimation can be performed by means of different *NN* architectures *(Simani, Fantuzzi, 2000; Simani et al., 2002).* In particular, *NNs* can be used as *function approximators* to estimate single sensor *fault size*. *(Puig et al., 2007)* gives a good presentation on various *NNs* application in *FDi* of chemical process and plants. A large number of *NN* architectures in use such as *MLP*, *RBF*, *etc.*, are among the most frequently used structures for *FDi*. Recently *DNN* was successfully applied for *FDi (Cheol et al., 2010).* It allows improving fault prediction accuracy of *CM* systems. *(Mirea et al., 2008)* investigates the development of a new type of *recurrent wavelet network* and its application to *FDI* of a dynamic process. A neural *Generalized Observer Scheme (GOS)* is used to generate the *residuals* (symptoms) in the form of one step-ahead prediction errors.

IV.3.2.1 - Residual Evaluation

In *FDI*, before applying the *NN* for the *residual evaluation* and *analysis*, *first*, the *residual* must be existing under the form of *data base* known as *fault signature*, generated with *NNs* or with any other approach, and then the *network* has to be *trained* by examples for this evaluation task. After *finishing training*, the *NN* can be *applied* for *on-line residual evaluation (Chen et al., 2003).*

IV.3.2.2 - Classification

NNs have been usually used very successfully in *FDi* to *classify* different input patterns into different classes and therefore classify faults present in measurement according to the operation of the process *(Simani, Fantuzzi, 2000; Evsukoff, Gentil, 2005).* For this reason, recently, *NNs* have emerged as potential tools in the area of *FDi* because of their capability to learn the features of different fault *classes* from examples, and their demonstrated ability as robust *classifiers* (Zhang, Roberts, 1992). Few literature studies had acknowledged the efficiency of *NN* as *PR* in *FId* and *FDi* (Ab. Rahman, 2010). After training, the learnt *symptom-fault relationships* are stored as the trained network weights and the network is ready to be used to classify the symptoms into the corresponding faults. In (Kannan, Rathinam, 2012), a *classification* of *high impedance faults, HIFs,* has been done with *six NNs* namely *Back propagation network*, *cascade correlation network*, *RBF*, *learning vector quantization*, *NARX network* and *adaboost classifier. FFNNs* have been used primarily as a *transient classification* tool to detect and *identify* a set of pre-specified *component failures* (Reifman et al., 1996).

In some applications, the *classification* is based on the *processing* or *evaluation* (Srivastava et al., 2014) of the *residuals* (Becraft, Lee, 1993) and it is used as *PR* (Srivastava et al., 2014) for *FId* in *FDi* (Simani, Fantuzzi, 2000) which consists to identify all faulty modes behavior (Venkatasubramanian, Chan, 2002; Racoceanu, 2003; Borguet, Léonard, 2009). (Baughman, Liu, 1995) have mentioned that networks with *one hidden layer* show their ability to effectively *identifying* process faults using feature *classification* (Ab. Rahman, 2010).

In (Yu et al., 1999), *FIso* is implemented by *RBF network* as a *classifier*.

IV.3.2.3 - Pattern Recognition

In the context of classification, recently, *NNs* have been used successfully in *PR* and they have been advocated as a possible technique for *FDi* too. (Keller et al., 1994) have presented the application of two *NNs (MLP* and *linear associative memory networks* where all neurons have linear activation function), in *shape recognition* for *FDi*. (Patel, Patel, 2015). In (Anzurez-Marin, 2014) the isolation problem is formulated as a *PR* problem, was solved using *BP network. NNs* are used for *FIso*. The *event detection* can be considered as *PR* problem.

For instance, *FFNN* might incorrectly give a *classification* answer with high confidence for a new type of transient on which it has never been trained (Bartal et al., 1995). *FFNN*s have been used primarily as a transient classification tool to *detect* and *identify* a set of pre-specified component failures (Reifman et al., 1996).

When an event occurs starting from the steady state operation, instruments' readings develop a time dependent pattern which is unique with respect to the type of an event. Therefore, by properly selecting the plant parameters, the *Initiating Events* (*IEs*) can be distinguished. To tackle this problem, a number of *linear* and *NL PR techniques* can be used. For this work, *NNs* will be used for event identification. Since the *NNs* cannot be trained on all possible *IEs*, it is important that it does not classify the *IEs* on which it has not been trained. Otherwise, the system will wrongly classify the patterns that it does not know (Bartal et al., 1995).

IV.3.3 - Hybrid Methods

In addition to *stand-alone NN-based systems*, some authors have concluded that the most effective *NN* methods in numerous *monitoring* applications are the *use* of *more than one networks* and their *combination* with other advanced *computational* tools as *hybrid systems* (Palade et al., 2002; Zhou et al., 2003; Evsukoff, Gentil, 2005). The purpose of the development of *hybrid monitoring systems* (Reifman, 1997b) is to enhance the substantial performance of the functionality of the *FM* algorithm to be more applicable to real industrial systems by taking advantage of the strengths of each individual technique and combine them for finally avoiding the weaknesses and alleviate some of the limitations of *NNs*. The role and responsibilities of each part of the *hybrid system* and how they interact must be clearly described. *NN*s are combined with other *AI* methods such as *FL*, *ES* (Reifman, 1997b) and *GAs* (Uhrig, 1991; Becraft, Lee, 1993; Srivastava et al., 2014); *SP* such as *WT*, *statistics* such as *PCA;* and *quantitative modeling methods* (*e.g., KF*) (Becraft, Lee, 1993).

NNs techniques are based on the existence of a learning database, as input variables which can be *quantitative* or *qualitative*, consisting of a set of measurements of different modes of operation, normal or abnormal, of the system to be monitored. In the safety-critical processes, data must be first *validated* before any work is to be done using these data. Although *NN*-based *FDi* tools can tolerate a certain degree of corruption or incompletion in data input. When the output of the *NN* represents the state of the considered system, the problem of monitoring can be considered as problem of *PR*. The form to be recognized is characterized by the set of data (*quantifiable* and / or *qualifiable*) and the membership classes representing the different modes of operation. The *NN* can then inform us about the operating state while ensuring both the *FDe* function (normal operation or not) and the *FDi* function, since it specifies the failure mode.

Depending on the quality of input measurements and recurred results, these measurements are either fed directly to the *NN*s based monitor or they are first *preprocessed* or *conditioned* to reduce the effect of noise and disturbance *(Srivastava et al., 2014).* Also, for improving the network training step, it is preferable to *normalize* the set of data before being input to the *NN (Grigoryan, 2015).* On other hand, the post-processing is considered as a way of increasing network reliability *(Santana et al., 2012).*

In *NR*, particularly in control room, there are many *parameters* (*variables*) which indicate the plant status operation. Thus, it is important to choose the smallest possible *parameters* numbers that have some degree of coherence with each other and contain the most necessary information for *NN*s to monitor a plant. Therefore, it is interesting to have an automatic selection method of optimal inputs (*e.g., GAs)* and consequently, the obtained results will be a faster training time *(Uhrig, Guo, 1992).*

KBTs acts as the overall controller in the monitoring process, interacting with the user, retrieving sensor measurements and other data directly from the system being diagnosed as well as from the plant operator, running the *NN* module, interpreting the *NN* results and performing any necessary *post-processing FDi* reasoning before providing a *FDi* to the system user.

(Ngaopitakkul et al., 2011; Patel, Patel, 2015; Perez et al., 2016) presented the application of *wavelet multi resolution analysis* in combination with *NN* for accurate *classification of faults* in *transmission lines*. *Filtering* and *analysis* of this *high frequency* spectrum is done using discrete *WT*. The *NN* is used to *classify* faults considered as spectrum pattern characterized by a band of frequency changes and depends on the location of fault in the transmission line.
(Kannan, Rathinam, 2012) have presented the *High Impedance Faults* (*HIFs) detection* based on *six* different methodologies of *combination* of *WT* and *NNs*. This *FDe* is made in *two stages*. In the *first stage*, the current signals of the feeders are *analyzed* using *WT* to obtain the relevant data signals. In a *second stage*, the properly trained *NNs* are used as a *classifier* processing, in order to classify the state of each feeder. Authors conclude that the methods which give accurate classification in less time among the mentioned methods are combination of *wavelet entropy* and *RBF*, *wavelet entropy* and *BP* network, *wavelet entropy* and *cascaded back propagation network*, *WT* and *Learning vector quantization*. The method which uses the combination of *wavelet* entropy and *NARX* networks takes more time in classification though the accuracy is very high as previous methods. These methods given accurate *classification* in less time, knowing that time and *accuracy* are two things to take into consideration.
(Ngaopitakkul et al., 2011) used a combination of *DWT* and *RBF network* to identify the fault type in underground cable. *DWT* was used in order to decompose high frequency components from fault signals. The *RBF* network was divided into two case studies training for comparison between classification of fault type and identification of the phase with fault appearance.

Monitoring can be performed by means of *NNs* and *DTs* were also presented in numerous works *(Sugumaran et al., 2007; Maji, 2008). (Kourd et al., 2013)* presented a new technique of *FDI* based on *NNs fault-free* and *faulty behavior models* used for *residual* generation, while *DTs* are introduced for *residual selection* and *evaluation*.
(Sreedhar et al., 1992) investigated the use of *NN*s and sliding observers for *FDe* in a thermal power plant. The *NN* and *KF* schemes for *SeV* were proposed for flight control systems.

PR techniques are also *combined* with *NNs* in developing dedicated models for different operating regions of a power plant *(Fantoni, Mazzola, 1996).*
(Teles, Seixas, 2002) have used *MLP* and *PCA* for the detection of failed (fissured) rods, within a nuclear fuel assembly by sounding the rods with ultrasonic pulses and examining the received echo waveforms classifier. The *MLP* is used as classifier and the *PCA* is used as data compaction for reducing the network's input with no efficiency loss.
When using *NN* in combination with *KBTs*, such as *fuzzy set theory* and *ES*s *(Gafoor, Ramana, 2006; Chiradeja, Pothisarn, 2009),* adaptation (interpretation) between them is necessary. *NNs* require interpretation of their outputs before a *FDi* can be made and are unable to explain their reasoning methodology *(Reifman, 1997b).* This integration with *NNs* technology is used individually *(Palade et al., 2002)* in *FDe* and *FDi* or both *(Nozari et al., 2011).* Thus, if the symptoms of the *FDi* task are numeric values, such as sensor measurements, the *NN* module should logically be placed in front of the *KBT*, thus taking a *NN* as *numeric*-to-*symbolic preprocessor* approach. If the *FDi* symptoms are symbolic in nature, such as commonly occur in medical diagnoses as well as alarm states in plant *monitoring*, the data should pass through the *KBT first*. The input symbolic data are then converted by the *ES* to equivalent numeric values useful for *NN*. Hence, the *KBT* is used as *symbolic-to-numeric* preprocessor. So, the combination of *NNs* and *KBT s* in a two-level hierarchical architecture has been reported by different researchers. This integration exhibited good *FDi* performance under a variety of conditions including *novel faults* and the presence of *sensor noise*.

Fuzzy reasoning is able of handling uncertain and imprecise information, while an *NN* is able of learning from examples. In order to make model-based *FM* algorithms more applicable to real industrial systems, *NNs*, *fuzzy* sets or their combination (*NF*) can be considered. The combination of *NNs* and fuzzy systems can be done in two main ways; *NNs* are the basic methodology and *FL* is the second and *FL* is the basic methodology and *NNs* the subsequent *(Palade et al., 2002).* From an engineering point of view, much of the interest in *NNs* and *fuzzy* systems, named *Fuzzy Neural Networks (FNNs),* has been used for dealing with difficulties arising from uncertainty. *FNNs* intend to combine the advantages of both *fuzzy* reasoning and *NNs*. Several *FDi* researches based on various types of fuzzy *NNs* have been studied *(Wang, Keerthipala, 1998; Javadpour, Knapp, 2003; Zhang et al., 2003). (Zhang, Morris, 1996; Wang, Keerthipala, 1998)* have proposed *FDi* methods using *fuzzy models* implemented by a special type of *NNs*. *(Zhang, Morris, 1996)* has proposed a process modeling and *FDi* using *fuzzy* models implemented by a special type of *NNs* which combine the capability of fuzzy reasoning in handling uncertain information and the capability of *NNs* in learning from examples. The main drawback of *NNs*-based *FM* is their lack of transparency in human understandable terms, represented by their *black box* nature, while the disadvantage of fuzzy systems is represented by the difficulty and time-consuming process of knowledge acquisition. On the other hand, the advantage of *NN* over fuzzy systems is learning and adaptation capabilities, while the advantage of fuzzy system is the human understandable form of knowledge representation. *NNs* use an implicit way of knowledge representation while fuzzy and *NF* systems represent knowledge in an explicit form, such as rules. *(Evsukoff, Gentil, 2005)* presented an application of recurrent *NF* systems to *FDI* in *NRs.* In *(Palade et al., 2002), NF* techniques were exploited for both *residual* generations for *FDe (Nozari et al., 2010)* and *residual* evaluation for *FIso* of actuator fault in an industrial gas turbine. *(Uçar et al., 2009)* have applied *FL* and *NN* for *alternator FDe*. *(Javadpour, Knapp, 2003)* have proposed a fuzzy *NN*-based *CM* by using fuzzy *ARTMAP*. In *(Zhang et al., 2003),* fuzzy *NNs* based on *bidirectional associative memories* have been proposed for *FDi* system of *rotary machines FM*. *(Zhang, Morris, 1994)* were using fuzzy *NN*s method for on-line process *FDi. (Wang, Keerthipala, 1998)* presented a new approach to real-time *FM* (*FDe* and *Classification*) in power transmission systems by using *fuzzy-neuro* techniques. *(Evsukoff, Gentil, 2005)* presented an application of *recurrent NF* systems to *FDI* in *NRs*. The *NN* is adapted to the recognition of the dynamic evolution of process variables and related *faults*. Process data is fuzzified in order to reason on qualitative rather than on quantitative values. *(Palade et al., 2002)* have focused on the application of *NF* techniques in *FIso* in industrial gas turbine. *(Adouni, 2013)* have presented a scheme for *FDI* of sensors and actuators in an induction machine in which the generation of *residual* for the *detection* phase is based on *NN* and the *residual* analysis is made with *FL.* The obtained results shown that *actuator* and *sensor* fault are *detected* and *isolated* successfully. *(Nozari et al., 2010)* have used *Local Linear NF* for robust *FDe* of *NL* systems with application to a *gas turbine engine*. *NF* techniques were also exploited for both *residual* generation and evaluation in *detection* and *isolation* of *actuator* fault of an industrial gas turbine *(Palade et al., 2002; Nozari et al., 2010). (Khireddine, 2014)* proposed *NF FDI* scheme based on a two-step procedure: a *NARX* network model is used for *residual* generation and a recurrent fuzzy *NN* performs the *residual* evaluation task. *(Evsukoff et al., 1999; Alexandru et al., 2000)* have been successfully used *recurrent NF networks* for the *FDi* of a simple electrical motor.

*ES*s can obviously provide a useful post-processing function for *NN* diagnoses, providing a more natural user-interface, interpretation and explanations regarding their reasoning. As *NNs* are basically, numerical algorithms, the inputs and the outputs to the *NN* subsystem will be numeric, as well. *(Becraft, Lee, 1993)* developed an *artificially intelligent* system, composed of *ES*s and *FFNNs*, for the *FDi* in large-scale chemical process plants. The *NN* is used as a first-level filter to *diagnose faults* commonly encountered in *chemical process plants*. Once the faults are localized within the process by the *NNs*, the deep knowledge *ES* analyzes the results, and either confirms the *FDi* or else offers an alternative solution. *(Nabeshima et al., 2002)* presented a hybrid *monitoring* system for *NR* using *NNs* and a rule-based real-time *ES.* The *NN* is used to *model* the plant dynamics with normal operation data and to *detect* the symptoms of anomalies. The real-time *ES* is used in *diagnosing* and displaying the system status by using the outputs of *NNs* and a priori knowledge base. *(Reifman et al., 1996)* suggested the use of an *ES* followed by an array of *NNs* where the purpose of the *ES* is to generate hypothesis about the possible failures which are then tested by an array of networks to *identify* the faulty component from the hypothesized candidates. In contrast. *(Becraft, Lee, 1993)* have developed an artificially intelligent system, composed of *ES* and *FFNNs*, for the *FDi* commonly encountered in large-scale *chemical process plants*. Once the faults are *localized* within the process by *NNs*, the deep knowledge *ES* analyzes the results. Finally, the researches *have* shown that the *FDi* methods *integrating NNs* with *ES* is superior, compared with the individual *ES* and the *fuzzy diagnosis system (Neto et al., 2009; Sadeghian et al., 2009; Chen et al., 2011).*

They can be used to find approximate solutions to numerical optimization problems in case where finding an exact *optimal solution* to complex problems, is prohibitively expensive. *(Gao et al., 2000)* proposed a system that uses *Elman's nets* based motor *FDe* scheme with a *training-aided GA*, further introduced to improve the approximation accuracy, and achieve better *FDe* performance. *(Bo et al., 2010)* have applied hierarchical *GAs* to determine the structure and parameters of *NNs* used to three-phase inverter circuit *FDi*. *(Jain et al., 2015)* used *GAs* and *NN* for gear *CM.* The selection of input features and the number of nodes in the hidden layer are optimized using a *GA*-based approach.

The *FDI* technique was developed by integrating two successful data-driven methods, *PCA* and *NN* by *Zhou et al., 2014).* In *(Khaled et al., 2010)* a hybrid system was demonstrated that combines *NNs* with *PCA* to *identify* and *isolate* faults. In some cases, *PCAs* are also used for dimension reduction in the process of model identification through *NN*s *(Weerasinghe, Gomm, 1998; Hadad et al., 2008). (Leger et al., 1998)* examined the feasibility of using *NN*s combined with statistical control charts (*CUSUM*) for *FDD*.

IV.3.4 - Advantages of NNs in Monitoring

The incorporation of the *NNs* into the monitoring domain may yield great benefits in terms of *speed*, *robustness*, and *knowledge acquisition*. More recently, the potential of *NNs* for *monitoring* has been demonstrated *(Catelani, Fort, 2000; Shen et al., 2002).*

For applicability to *FM*, the *NN* features are important *(Napolitano et al., 1995)* and give capabilities to provide real-time responses.
Last two decades, a great deal of attention has been paid to the application of *NNs* for *FM* issues *(Calado et al., 2001; Korbicz et al., 2004).* This is due to the *great capabilities* and *advantages* of *NNs* which leads as decision support systems and represents an important solution for *CtM* of complex and *NL* plant parameters *applications (Elnokity et al., 2012; Lakshmanan, Posonia, 2016),* because *NNs* provide an excellent mathematical tool for dealing with *NL* problems *(Kourd et al., 2013).*

NN is an effective alternative for performing system *FDe* while *avoiding* the need for a *MM*. *NNs* are one candidate which is not only able to *tackle NL systems*, but are also developed from data without the need of model specifications (*i.e.,* they are *data-driven*). *(Marcello et al., 1998)* has presented a *comparative,* at linear dynamic conditions, of the performance between a bank of *KF-based* and an *NN-based scheme* as on-line state estimators for *sensor FDIA* scheme in a *flight control system*. The comparison is performed through testing of *FDIA* capabilities of the schemes for several types of *failures* presenting different levels of *complexity* in terms of *detectability*. Authors conclude that while the *KF*-based scheme takes advantage of its robustness capabilities, on-line learning neural architectures have potential for on-line estimation purposes in a *SeV* scheme, particularly in the case of poorly modeled dynamics. Over the past *decades* many *FM* publications have targeted fixed *model-based* approaches, with *parameter estimation* and *observer-based* methods being the most popular. This is why the use of *NNs* with *online learning* capabilities is steadily growing in the *FDe field (Isermann, Ballé, 1997).* So, the drawback of *MM-based* approaches can be avoided by taking advantage of the flexible learning and generalization capabilities of a *NN* and make *FDe* algorithms more applicable to real systems.
A *second desirable* feature of *NN is* their highly *parallel structure* allowing them to achieve a higher degree of *FTo* then conventional schemes *(Hunt et al., 1992).*
Online training of *NN* makes it possible to change the *FM* system easily when changes are happening in the *physical process*, *control system* or *parameters (Becraft, Lee, 1993; Srivastava et al., 2014).*
So, *NNs* are able to *detect* the symptoms of small anomalies earlier than the conventional alarm system *(Nabeshima et al., 1998).* The majority of the reviewed articles discuss the *FM* performance of *NNs* with noise added to the data *(Xing, Okrent, 1994; Reifman et al., 1996). (Jeong et al., 1996)* and concluded that *NNs* can successfully classify transient events when a 10% noise (equivalent to approximately 3 standard deviations) is present in the data. The results also indicate that *NNs* trained with input noise appear to become less sensitive to input noise in the test data *(Bartlett, Uhrig, 1992).* The intrinsic ability of *NNs* to *filter noisy data* while preserving its structure and detail is perhaps one of the major advantages of using *NNs* for *FDId (Reifman, 1997b).*
Other desirable feature of *NN is* their ability to respond in real-time to the *changing system state* descriptions provided by continuous sensor input. For complex systems involving many sensors and possible fault types (such as *NPP*s), real-time response is a challenge to both human operators and *ES*s *(Uhrig, Guo, 1989).*

IV.4 - Fault Control

The *FDA* is an implementation as *FDe* and *FA*. At *FDe* stage, a *FAl* is triggered if the *residual* exceeds its threshold then; the faulty sensor measurement is replaced, at *FA* stage, with a reliable model estimate, a reasonably close value to the original one and the system such as the *control loop* can remain operating even with multiple sensor failures. Sometimes, the use of estimation for *FA* is not possible such as with *KF (Khentout et al., 2018).* However, the *system* will continue operating by using the most recent corresponding output which is a good estimation of the failed sensor measurement. In *Figure IV.14,* the estimation is made by *NN* and once a faulty sensor measurement is *detected*, it will be *disconnected* from the input layer of the network so that the output is the estimation instead of the sensor measurement.

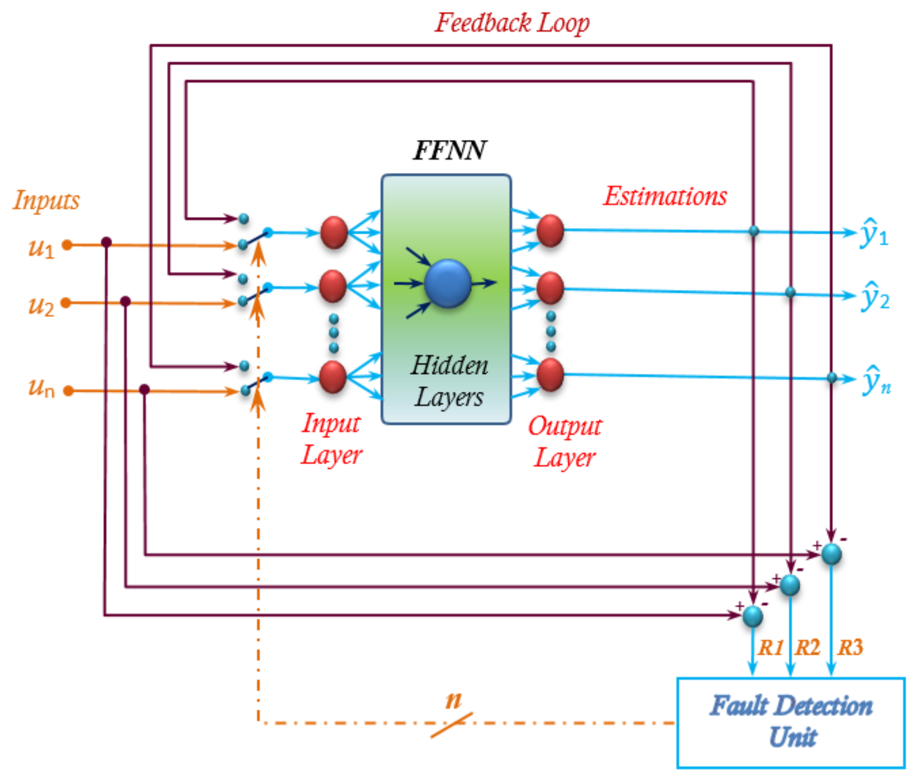


Figure IV.14 - FFNN for accommodation.

Traditional approaches to *SeV* involve periodic instrument calibration which present many drawbacks. An *alternative*, *NN*, offers several advantages *(Upadhyaya et al., 1990; Eryürek, Türkan, 1991). AANNs* are widely used for *SeV* because of their capability to *detect fault* and *reconstruct* the *original signal*. These *NN* are discussed and implemented with various algorithms in *(Guo et al., 2003; Guo-Jian et al., 2010).* In *(Shah et al., 2013), AANN* is used for sensor *FDid*, *FDiso* and *reconstruction*. *(Duane et al., 1998)* have presented two approaches to the *SeV* problem; a *model-based approach* using an *AANNs* and a *NL observer* which used functional *approximation NN*s to model the variation of the system at the operating point. In recent *SeV* studies, the *AANN* has been used *(Zedda, Singh, 1998).* The use of *AANNs* approach for *SeV* has often been proposed by *(Kramer, 1992)* and used subsequently by other researchers *(Hines et al., 1998). (Hines et al., 1997a)* have used *AANNs* to instrument monitoring and calibration monitoring for *SeV* at *Florida Power Corporation's Crystal River 3 NPP* and at the *Oak Ridge National Laboratory High Flux Isotope Reactor*. *(Uluyola et al., 2001)* presented an *AANN* approach to *SeV* for an aircraft engine. *(Guo, Musgrave, 1995)* used an *AANN* for *SeV* of a rocket engine and indicated that the *NN estimates* of the sensor values could be used to *replace failed sensor* values in a feedback control system. *(Mattern, Jaw, 1998)* presented the results of applying *two* different *types* of *NNs* in two different approaches to the *SeV* problem. The *first* approach uses a functional *approximation NN* as part of a *NL observer* in a model-based approach to *AR*. The *second* approach uses *an AANN* to perform *NL PCA* on a set of *redundant sensors* to provide an *estimate* for a single *failed sensor*. *(Guo, 1996)* used an *AANN* for the *SeV* of the *F100* turbofan engine. In this *network*, the *redundant sensor information* is *compressed*, *mixed* and *reorganized* into a smaller number of nodes in the *first part* of the network. The compressed information is then used to regenerate the original redundant data at the output. Due to the information mixture, if a sensor fails, other sensor data still provide enough information to generate a good estimate to replace the faulty measurement. *(Uluyola et al., 2001)* used *AA* and *hetero-associative NNs* together to provide *validation* for *pressure* and *temperature sensors* and then *FDId* for these sensor faults. In *(Nabeshima, 2005),* the *NN of monitoring aids (NNMOA*) system is applied to the *CM* and *SeV* of *multi-purpose reactor* (*RSG-GAS*) in Indonesia. The *FFNN* in *auto-associative* mode learns reactor's normal

operational data and models the reactor dynamics. The on-line test results showed that the *NN* successfully monitored the reactor status during power increasing and steady state operation in real-time.
(Böhme et al., 1999a) proposed an approach based on the use of *SOM* *(Kohonen, 1995)* for multi-parameter *data validation* and *reconstruction* of data.

As an alternative to traditional model-based *SFDA* schemes which rely on an analytic *MM* of the real system, *NN-based SFDA* schemes have received a huge amount of research interest over the past decade *(Isermann, Ballé, 1997).* They have been successfully designed and tested on a variety of engineering systems *(Blanke et al., 2003; Samy et al., 2008; Samy et al., 2010).* In an attempt to widen the scope of *NN-based SFDA* schemes, *(Samy et al., 2008)* have designed and applied such a scheme to a *NL UAV* model. The *NN* structure chosen is based on the *extended-minimum resource allocating RBF network* due to its *good generalization ability* and *fast performance* *(Li et al., 2000). (Samy et al., 2010)* proposed two schemes for *SFDA*; one is based on a *NN* and the other on an *EKF*. The objective was to compare both approaches in terms of execution time, robustness to poorly modelled dynamics and sensitivity to different fault types. Results have shown that the *NN-SFDA* scheme outperforms the *EKF-SFDA* scheme with good missed fault, zero *FAI*s and an average estimation error for different test conditions. *(Böhme et al., 1999a)* investigates the potential and demonstrates the accuracy of *two* different *NN* approaches, five-layer *MLP* with a global feedback loop and *SOM,* for *signal FDe* and *reconstruction (SFDR)* using real data. It is established that *both methods* are able to *reconstruct* single soft failure as well as two consecutive faults but the *reconstruction* quality becomes poorer if more faults occur consecutively.

When *NNs* are used in *FDIA* and once a faulty sensor measurement is *detected* and *identified*, it will be *disconnected* from the input layer of the network for the purposes of isolating the *false information*. Many approaches proposed, developed and documented in recent research literature; implement *NN*-based *AR* as an *alternative* approach *of MMBT* for *FDIA* *(Perhinschi et al., 2007; Samy et al., 2008).* Also, there has been an increasing interest in the application and development of *NNs* for *SFDIA* and *Actuator FDe, Identification and Accommodation (AFDIA)* schemes and an important implementation has lately been proposed and developed *(Samy et al., 2010*; *Silva et al., 2012*; *Gururajan et al., 2013). (Palmé et al., 2011)* has demonstrated a complete solution for *SFDIA* through employing *NN* as a *classifier* in combination with *NNs* configured as a *regression* networks for the production of soft measurements. *(Napolitano et al., 1995)* presented a *NN*-based approach for the problem of *SFDIA* for a *flight control* system without *HR* in the sensors. In *(Hussain et al., 2013),* the *Neuron By Neuron (NBN)* learning algorithm, considered as an improved version of the *Levenberg-Marquardt (LM)* algorithm is combined with the *Fully Connected Cascade* (*FCC) NN* to develop the sensor estimators of an aircraft. These estimators can be used in any *SFDIA* scheme to provide the *FAc*. *(Guo, Musgrave, 1995)* have used *AA network*, trained using the *BPA*, in *SFDIA* scheme for sensors in the *Space Shuttle Main Engine* (*SSME).* The *AA network* architecture has also been used for *FDe* in intelligent sensors *(Rajendran et al., 2013; Huang et al., 2007). (Napolitano et al., 2000)* developed an *SFDIA* scheme using the hetero-associative *MLP* trained using the *extended BP algorithm (EBPA).* This scheme was evaluated on sensors. *(Samy et al., 2008; Samy et al., 2011)* proposed an *SFDIA* scheme using the *RBF network,* trained using the *EMRAN* algorithm. In *(Campa et al., 2002b)* a *NN-based scheme* for *SFDIA,* implemented with different *neural approximators, MLP* trained with the *EBPA (MLP-EBPA)* and *RBF network* trained with the *EMRAN (RBF-EMRAN*), has been analyzed using experimental flight data of a research aircraft model of a *B*777 and the performances were compared. *(Napolitano, 1996)* has presented a comparative study of performance between a *KF*-based and a *NN-based scheme* used for *SFDIA* in a *flight control system* assumed to be without *HR*. In *(Napolitano et al., 1999),* the *performance* of the *NN-based SFDIA* scheme was *compared* with the performance of an identical scheme with *KFs* instead of the *Main Neural Network* (*MNN*) and a *set of n Decentralized Neural Networks* (*DeNNs*). This comparison showed the advantages of the on-line learning by the *NN-SFDIA* scheme vs. the robustness of the *KF SFDIA* scheme for modeling discrepancies between the actual system and the filter model; additionally, the study showed a similar level of computational effort for on-line applications.

IV.5 - NN Applications in Fault Supervision

Over the past decades, there has been an increasing interest and a great deal of attention has been paid to the application of *NNs* for *FM* issues *(Kourd et al., 2013)* and accommodation schemes *(Napolitano et al., 2000; Samy et al., 2010).* The fields of *FM* and control systems have benefited from the application of *NNs (Hong et al., 1999). NNs* show great promise for use for *FM* in environments in which robust, *FTo*, a good classification, *intelligent decisions* and recognizing faulty component patterns are necessary to achieve in a real-time with higher degree than conventional schemes *(Reifman, 1997b).* Nowadays, the vast number of applications has raised significantly. The *potential applications of NNs* include, but are not limited to: (*a*) *diagnosing* specific abnormal conditions, (*b*) identification of *NL* dynamics and transients, (*c*) *detection* of the change of mode of operation, (*d*) control of temperature and pressure during start-up, (*e*) *SeV*, (*f*) plant-wide *monitoring* using *AANNs*, (*g*) *monitoring* of check valves, (*h*) modeling of the plant thermodynamics, (*i*) emulation of *core* reload calculations, (*j*) analysis of temporal sequences in *NRC*'s licensee event reports," and (*k*) *monitoring* of plant parameters. The vast majority of the proposed systems for *FM* use the *FFNN architecture* with different variations of the *BP* training algorithm. *(Koivo, 1994)* presented a good synthesis on the application of the *NN*s in industrial *FM*. It gives the neuronal architectures the most used in this domain with practical results in statics and dynamics monitoring applications. Other references for application of *NN*s in *FM* can be found in *(Liang et al., 2001).*

IV.5.1 - Instrumentation

Seen the limitation of space, we are limited to main two instrument, sensor and actuator, usually intensively used in plant and particularly in *NR*s.

Many works are used *NNs* methods to adopt the *detection sensor/actuator faults* for various systems as presented in *(Talebi et al., 2009; Samy et al., 2009).* Sensor and actuator fault are detected and identified using *AR* as presented in the different works *(Zhirabok, 2008; Hajiyev, 2012). (Adouni, 2013)* have used *NN* successfully for the detection and *FL* of sensors and actuators fault in an induction machine. *(Gang et al., 2013)* used a system model-based on *MLP* with dynamic neurons in the state-space representation for the actuators and sensors *FM*. *(Baraldi et al., 2011b)* addressed the problem of *reconstructing* the correct *signal* values measured by *faulty sensors* in *NPPs*. One practical approach to effectively handle the dimensionality of the problem due to the large number of sensors typically involved is offered by resorting to an ensemble of *AA* models for signal reconstruction. *(Du et al., 2014)* presented a dual *NNs* combined strategy to *detect* the *faults of sensors (Xin et al., 2015). (Naidu et al., 1990)* studied a *sensor FDe* system based on *MLP* and *back-propagation learning algorithm*. They also discussed traditional *FDe* algorithms. *(Böhme et al., 1999a) constitutes* an application of two different *NN* approaches, *AANN* and *Kohonen*, for *FDe* and *reconstruction* of *sensors'* faults in a water treatment plant. *(Mandal, 2015)* proposed an online *sensor FDe* scheme in *NPP*s by *NN*. The method is validated using data from *Fast Breeder Test Reactor*. Compared to all other methods, he concludes that this method is robust and reduces the spurious/*FAl*. In *(Li et al., 2007; Talebi et al., 2009)* a *DNN* was used to *detect actuator faults* in the attitude control subsystem of a satellite. In *Daneshnia et al., 2016) DNN* with an internal feedback is applied for *FDe* of boiler-turbine *actuators*. In *(Guo, Nurre, 1991)* two networks are proposed to detect sensor failures and Recover the lost measurements from a group of redundant sensors. The *NN* structure selected for this task is a *FFNN* with the sigmoidal activation function for each node. The first network is trained to detect the sensor which is inconsistent with other sensor readings. The second *NN* is to perform the recovery of the measurement due to the failed sensor. A back-propagation algorithm is used here to train the *NN*s. The scope of this study is limited to the sensor *FDe* during the nominal operating condition. The proposed scheme is tested using the simulated data of the *SSME* inflight sensor group.

IV.5.2 – Systems, Equipment and Processes

In this thesis, we are limited to three main systems, equipment and process, well known in *NR*s which are *HE*s, *core* and *rotating machinery*.

IV.5.2.1 - Heat Exchanger

It is difficult to study the performance of *HE*s experimentally because of the variety of parameters involved in the physical structure of the *HE*. Therefore, the application of *NNs* appears to have potential for *CM* of a *HE* even for situations in which there are substantial variations in the composition, temperatures and *FR*s of the individual fluid streams. *NNs* can offer an attractive method for *identifying* both *sudden* and gradual *degradation* in the *performance* of complex multiple *HE* systems. The *NNs* were able to *predict* the *overall* characteristics of the *HE* with a high degree of *accuracy* and in this respect were found to be superior *over* conventional *NL regression* models in capturing the underlying *nonlinearity* in the data. NN has been applied to many *thermal* problems *(Sen, Yang, 2000),* including the *prediction* of the *steady-state (Dõaz et al., 1999)* and the *dynamic behavior* of *HEs (Bittanti, Piroddi, 1997; Dõaz et al., 2000).* The *CRC handbook (Sen, Yang, 2000)* discusses usually the *applications* of *NN* and *GA* in *thermal engineering*. A handful of works has been done in the past to analyze the performance of *HE* using *NN*. *(Diaz et al., 1999) studied* in detail the *simulation* of *HE* using limited experimental data. *(Rui et al., 2006)* used a self-adaptive method using *NN* and presented a model for accurate simulation of *HE*s. *(Mohanraj et al., 2015)* applied *NN* for thermal analysis of *HEs*. *NN* techniques are extensively used to model the *NL* dynamic and complexity of *HEs* to predict the *overall* and detailed heat transfer *characteristics*. *(Tan et al., 2009)* used *NN* to predict the overall heat transfer of a *compact fin-tube exchanger* and he demonstrated how the *SOM*, can be used for *HE CM* by identifying and classifying the deterioration in exchanger performance.

Several authors have also used *NN* as an alternative *modeling method* for the *prediction* of *fouling (Riverol, Napolitano, 2005).* Online *fouling detection* and *estimation* of the *overall heat transfer coefficient* (*U*) were reported in literature *(Lalot, Lecoeuche, 2003). (Tan et al., 2009)* demonstrate how *SOM*, can be used for *HE CM* by identifying and classifying the deterioration in *HE performance* such as *fouling* or *sudden changes* in fluid, using data only from the *NOC*s. *(Yang et al., 2000b) predicted heat transfer coefficient* of fin-tube *HE* using *NN*. *(Mohanraj et al., 2015)* applied *NN* for thermal analysis of *HE*s. *(Mandavgane, Pandharipande, 2006)* have used *MLP* network with single hidden layer and 5 neurons as model of *shell and tube HE* to *estimate* successfully hot and cold temperatures as a function of *FR*s and concentration of fluids. *(Ramasamy, 2007)* developed and compared two different types of *NN*s models, *MLP* and *NARX,* for *predicting* the change in *outlet temperatures* over time in the *shell and tube* sides of the *HE*. He concludes that *NARX* model supersedes that of *FFNN* model. The aim of the work presented by *(Shekar, 2015)* is to predict the value of pressure drop for different inlet-outlet configurations of an air-cooled cross flow *HE* using *NN*. In *(Biyanto et al., 2007),* a *NN* model with *NARX* structure was proposed and developed to describe the complex behavior of a *HE* in *crude preheat train* (*CPT)* in a refinery. It was observed that the developed model has a good predictive capability. *(Shekar, 2015)* predict the pressure drop for a given configuration (inlet-outlet combination) and given mass *FR* for an air-cooled *cross flow HE* using *NN*. NN has been applied to many *thermal* problems *(Sen, Yang, 2000),* including the *prediction* of the *steady-state (Dõaz et al., 1999)* and the *dynamic behavior* of *HEs (Bittanti, Piroddi, 1997; Dõaz et al., 2000).*

IV.5.2.2 - Rotating Machinery

Rotating machineries are used in *NPs* in different manners as pumps of cooling circuits, motors, compressors and cooling fans which cool the control rod drive-mechanism. The motor parameters (*e.g., current*, *voltage*, *winding temperatures*, *etc.*) should be monitored in accordance with manufacturer's recommendations, industry standards and Practices, and plant experience. Different techniques are used rotating machinery mainly *vibration analysis*, *lube oil analysis*, *thermography* and *MCSA* *(Ronny, 2017).*
The *MLP* system is able to diagnose the faults that can be seen in most frequencies in starter motors. *(Bouzid et al., 2010)* used an *MLP* to *detect* and *diagnose* automatically, in a nearly stage, the *broken bars fault* in the *rotor* of the *induction motor. (Singh, Al Kazzaz, 2008)* developed an *MLP network* with *BP algorithm* for induction motor *monitoring*. *(Bayir, Bay, 2004)* presented a *FDi* system for a serial wound starter motor based on *MLP*. This *NN*-based *FDe* system has been developed for implementation on the emergency vehicles system. *(Cheon et al., 1993)* applied the *BP* network algorithm is to the training of multiple alarm patterns for the identification of faults in a *reactor coolant pump* (*RCP*) system *(Kaminski et al., 2011)* presented the application of *RBF* for the *induction motor rotor FDe* and conclude that this *network* can be an alternative to the well-known *MLP*-based *FDe. RBF network* is introduced into the *FDi* for *rotary machinery* and the result showed that an *RBF* network is able to correctly identify the various faults. So, *RBF* network has *good* practicality in the field of *equipment FDi. (Yi, 2010)* propose a *FDi* method based on *RBF networks* applied to air-conditioning *fan FDi*. The result shows that *RBF* network has very high learning convergence speed and better classifying performance. *(Bayir, Bay, 2005)* presented a *monitoring* system of *serial wound pre-engaged starter motors* by using a *Kohonen NN*. *(Uysal, Bayir, 2013) detected faults* in *switched reluctance motors* and *diagnosed* them in *real-time* with the *Kohonen's NN*. In *(Şekeret al., 2003), Elman's net*, is used for monitoring of high-temperature gas cooled *NR* and bearing damage condition in induction motors.

IV.5.3 - Nuclear Plants

On-line SeV and *CM* has become a significant issue to ensure stable operation and achieve higher plant operability. Especially, it is more important for *aged reactors* to detect the symptom of anomalies and deal with them at the beginning of serious accidents. *Reactors* are considered as *complex NL dynamics system* such that *classical MM-based* and other *conventional monitoring methods* are too heavy to use in real applications. *NN* applications play the major role in this field, specially, with their *model-free* structures and *powerful NL* properties. Hence, *NNs* are considered as a *powerful* and an *effective* technique in the *NPP FM,* and has a compatible structure with the real time applications. The emerging' technology of *NNs* offers a method of implementing real-time *FM* and *FDi* in *NPP*. Moreover, the *NN*-based systems can run very fast if hardware implementations are becoming available. This makes the systems, especially well appropriate for real-time applications such as alarm processing and *FDi* in *NPPs*. *IAEA* meeting on *NPP I&C systems* recognized potential usefulness of *NN* and recommended their development and implementation *(IAEA-TECDOC-952, 1997).* To get the satisfactory results in real time and for wide-range monitoring studies, *several application* studies of the *NNs* on *NPPs* have been carried out *(Türkcan et al., 1993). NNs* have been extensively used to *monitor* and *control* wide variety of *applications* studies of *NL* dynamic systems in *nuclear industry* have been carried out *(Türkcan et al., 1993).* These applications have all obtained satisfactory results in real time and for wide-range monitoring studies. They include, but are not limited to: prediction of *core* parameters *(Kim et al., 1993)* plant control and *monitoring (Uhrig, 1993) NL* dynamics and transient diagnosing *(Adali et al., 1997) signal prediction* and *SeV (Ikonomopoulos, Hagen, 1997)* diagnosing specific *malfunction* conditions detection of the changes of the operational mode *(Pazsit, Kitamura, 1996) component monitoring* and *event classification (Bartlett, Uhrig, 1992)* fuel management optimization *(Faria, Pereira, 2003)* and *system control (Uhrig, 1991).* A review of *AI* applications in *NPP FDi* and *FDe* by *(Reifrnan, 1977)* finds that mostly *ES* and *NN* techniques were researched and proposed. It reviews and classifies 95 publications (of which 33 were *NN*-based), and presents most of the issues that are involved in the AI-based applications in the *Pn* industry. *NNs* have a great benefit to the *NR monitoring*, apart from other numerous application areas *(Uhrig, 1991)*. *(Santosh et al., 2007)* presented a study on *various NN* algorithms for selecting a best suitable algorithm for *diagnosing* the *transients,* due to equipment failure, malfunctioning of process systems, *etc*., of a typical *NPP*. *(Uhrig, 1989)* has demonstrated the ability of *NNs technique* to *identify* the *causes* of perturbation in the steam generators of *NPP*. *(Roh et al., 1991)* have proposed the applicability of thermal power prediction. Also, the feasibility studies on the multiple alarms processing in electrical power systems have been reported in references *(Jongepier et al., 1991)*. Among several *methods (Kreider, Schneider, 1990)* to *detect failed rods* (fissured *(International Atomic Energy Agency, 1998; Teles, Seixas, 2002)* have used *MLP* classifier for the detection of failed rods, within *PWRs* fuel assembly by sounding *(Seixas et al., 2000)* the rods with ultrasonic pulses and examining the received echo waveforms. The classification was efficient with low false-alarm probability. *(Evsukoff, Gentil, 2005)* presented an application of recurrent *NF* systems to *FDI* in *NRs*. *(Abdul Rahman, 2010)* focused on the application of *MLP* to *monitor* the *faults* in a *Continuous Stirred Tank Reactor* (*CSTR*). *(Nabeshima et al., 1998)* gave how to use *NNs* for detecting anomalies of *NPPs* in operation and they used three-layered *AANNs* for *FDe* in real-time of *NPPs* in operation in real-time by using *AR*. The test results showed that this plant *monitoring system* is successful in *detecting* the symptoms of *small anomalies* in real-time over the wide power range including start-up, shut-down and steady state operations.

For *FM*, the input variables of *NNs* can be *quantitative* (*e.g.,* output of sensors), and/or *qualitative* (*e.g.,* observations made by the operator). From these input variables, the *NN* give outputs which can be an *estimation* or *classification* of monitored parameters *(Racoceanu, 2003; Srivastava et al., 2014)*. In many *FDi* problems of physical systems, such as *nuclear process plants*, the inputs to the *NNs* usually are *S/D measurements* and while each output neuron is a process alarm corresponds to one particular fault possibility.
(Gang et al., 2013) have presented a method based on integrated *NNs (INN*s), and *logical fusion* to improve the reliability of *FDi* in *NPP*s. Different methods of *NNs* were applied simultaneously. *(Gomm, Williams, 1995)* have applied The self-learning techniques for training a *RBF* network to learn and diagnose fault conditions from measured process data to the *FDD* of faults in a simulation of a continuous stirred tank reactor (*CSTR*). Related nuclear work includes the *monitoring* of the *Borssele NPP* using *NN* techniques is considered in *(Nabeshima et al., 1995; Ayaz, 2008)*. A *monitoring system* with various *NNs* has been developed for a *PWR* and implemented by *(Türkcan et al., 1993)* in the Netherlands. *(Seker et al., 2003)* addressed to the problem of use of the *NN*s for *anomalies detection* as well as physical parameters monitoring of *NPP* during power operation in real time. Three different types of *NN* algorithms were used namely, *FFNN* and two types of *RNN*s. The latest have shown a better performance than the first model. *(Böhme et al., 1999a)* constitutes a very interesting *NN*s application of *FDL* of *sensors' faults* in a *power plant*. *(Far, 2007)* presented an application of a *NNs-based* scheme for the *pressurizer* of a *PWR NPP*. More recently, researchers at *University of Tennessee (UT)* developed a *sensor monitoring system* for *Florida Power Corporations Crystal River* 3 *NPP* and *Oak Ridge National Laboratory's High Flux Isotope Reactor (Hines et al., 1996a)*.

In *(Upadhyaya, Eryürek, 1991)*, a *reactor power* is predicted by a three-layer *MLP* network by using *control rod position*, *core exit temperature*, and *intermediate HE secondary sodium outlet temperature* as *inputs* to the network. *(Pérez-Cruz et al., 2011)* proposed constrained *NN* control for the adaptive tracking of power profiles in the *TRIGA Mark-III* research *reactor. (Arab-Alibeik, Setayeshi, 2005)* proposed a neural adaptive inverse controller to control the core power of a *PWR* reactor. *(Pérez-Cruz et al., 2011)* proposed constrained *NN* control for the adaptive tracking of power profiles in the *TRIGA Mark-III research reactor*.

IV.6 - Conclusion

The model-based prediction assumes a fixed structure for characterizing steady-state or dynamic relationship among process variables. The generation of an accurate model requires time proportional to the size and complexity of the system. Relationship between signals in a subsystem of a plant can be modeled using *NN*s which provide results easily and faster than *MBTs* s if hardware implementations are becoming available. This makes the systems, especially well appropriate for real-time applications such as *Fault Monitoring and Accommodation (FMA)* in *NPs*. Generally, *NN*s can provide, in some cases, more interesting solutions than other monitoring tools, provided that the type of neural architecture is chosen wisely and, above all, that the learning phase is well conducted.

This chapter has been dedicated to the presentation of basic concepts *NNs* such as *neuron model; architectures; training; advantages* and *drawbacks.* We also treated the application of *NNs* for the monitoring of industrial equipment by using the recorded and online data acquired by *DAS* on supervision computer at control room. We distinguished that *NNs* are used into two different main ways: classification and identification. In the *first* type of application (*i.e.*, *classification*), the *NNs* associate an operation mode with each set of data (*i.e.* quantifiable such as sensor outputs or qualifiable such as observations on the system). In the *second* type of application (*i.e.,* system *identification*), *NNs* are used to give a *model* of the equipment in *black box* form. Nevertheless, through the list of non-exhaustive but representative references that we have consulted, we notice two temporal representations of the *NNs*: a spatial or external representation and a dynamic or internal representation. We showed that the *NN* architectures can be divided into two main categories; *static* and *temporal* networks. The latest, in turn, can be also classified into two groups; *dynamic* and *recurrent* networks. We have particularly detailed some architecture in each class.

An important criterion in monitoring is taking into account the dynamics of the system. This dynamic makes it possible to better identify the failure modes and to be able to anticipate the evolution of equipment (preventive monitoring). Therefore, we have addressed in this chapter a very important aspect to the *temporal* dimension in monitoring. We have given a state of the art as wide as possible of the different ways of taking into account this *temporal* aspect by the *NN*s, the different architectures of *temporal* networks and the way in which temporal learning are conducted. This study allowed us to conclude that there are many approaches of *temporal NN*s as well as works and publications concerning applications and architectures of *NNs*.

CHAPTER V

Results and Discussion

Based on historical data and online data during the normal and faulty operations of the process, the strategy of this chapter is to build a model of the process behavior and to use it in redundancy for detection and identification of abnormal situations process resulting from malfunctions in monitored, to help human operators in their decision-making. More specifically, the goal is to monitor, as early as possible, the failures of the process, by reducing the number of false alarms.

In this chapter we present a comparative result by using different analytical model-based methods (i.e., heat balance, ε-NTU, log mean temperature difference, Kalman filter) and neural networks for the detection, localization and accommodation of some parameter of the core and heat exchanger in Triga-Mark II research reactor.

V.1 - Introduction

Therefore, the strategy consists of two different but non-independent steps. A step off-line in which historic data are analyzed and treated to characterize the known behavior for the system, a second stage in which the behavior of the previously obtained process and the on-line data are used to determine the expected state of process.

In the present work, an experimental system is developed to investigate the performance of *HE* and some parameters of the core of the reactor. We applied the *mathematical estimation methods* described previously in *Chapter I* on the *shell-and-tube HE* situated between the primary and secondary cooling circuit of *Triga Mark II NRR* at *LENA,* with the purpose to predict its *temperatures* and *MFRs*. In this experience part, it is assumed that all internal *coefficients* of the *HE* are *known, constant* and *positive,* as given in *Table V.1.* The only *data* needed to be collected are the four *inlet/outlet temperatures* (T_{hi}, T_{ho}, T_{ci} and T_{co}) and *MFRs* ($\dot{m}_h$ and $\dot{m}_c$) at both streams of the *HE* unit. These parameters are all measurable in the case of the present *HE*. *Second*, we used *NNs* to estimate the four temperatures of the *HE* and also some parameters of the core of the reactor such as *Pn*, ρ and *Tf.*
The *FDA* software used in this experimental part is developed in *Matlab* and *Simulink* by exploiting *NN Toolbox* model, and executed for real-time monitoring (*RTM*) on portable *PC*. This software is chosen due to its capabilities and ability to provide solutions in technical computing.

The data used in this experiment as fault free are gathered from the *data acquisition supervision PC* at *LENA Reactor* (*Figure I.7*). One notes that these *training data* sets can be also extracted from the *system simulation* rather than the *real online data* acquired while the *reactor operates*.

V.2 - Estimation

V.2.1 - Analytical Methods for Estimation of HE Parameters

An *off-line experimental data set* taken at *LENA* reactor, particularly after the starting of the *cold* stream *pump,* is used with different methods for estimation. This *data set,* as shown on *Figures V.1 - V.3*, is composed of measurement of *temperatures* and *MFRs* of both fluids of the *HE*. In addition, this data set includes accompanying *Pn* to the associating operating modes of the reactor.

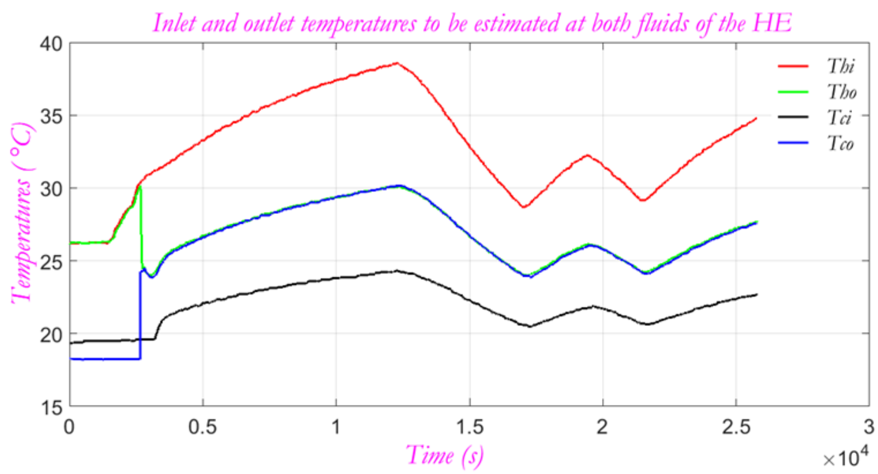


Figure V.1 - Global data set of inlet and outlet temperatures of the HE, used for the estimation.

On *Figure V.2,* we note that the cold fluid *pump* starts at time $k = 2654s$, the moment when the *outlet temperature,* T_{ho}, of the *hot fluid* reaches 30°*C* as shown by *Figure V.1.* Consequently, the *MFRc* jumps from 0 to 8.9 (*Kg/s*).

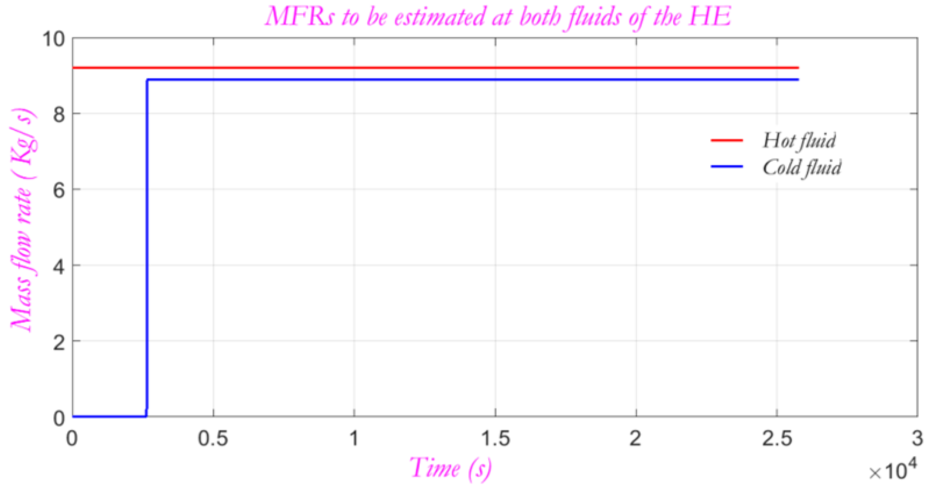


Figure V.2 - Global data set of the MFR of both HE fluids, accompanying the global data set, given on Figure V.1. Mean values at steady state for hot and cold fluids are 9.19 and 8.96 kg/s, respectively.

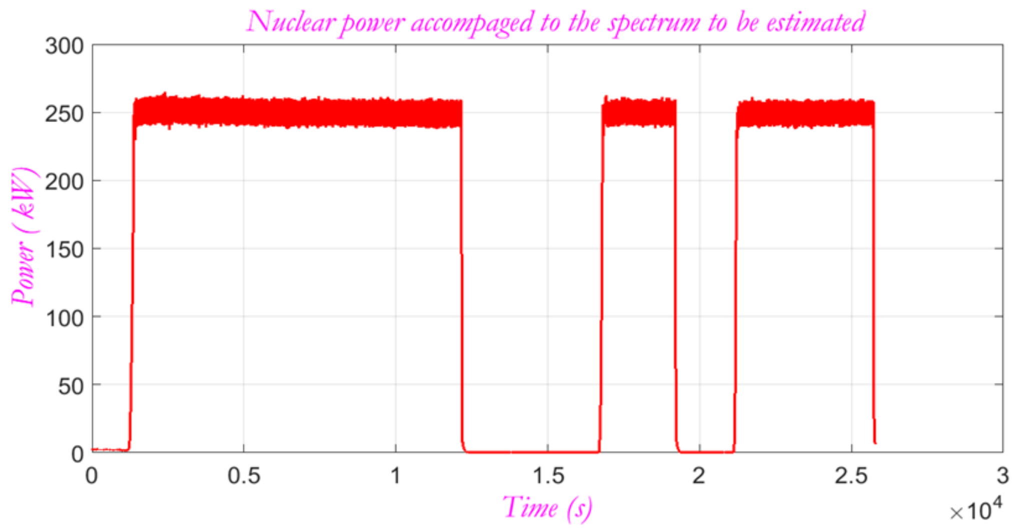


Figure V.3 - Pn accompanying the global data set, given on Figure V.1.

V.2.1.1 - Mathematical Methods

In this experiment, we distinguish two applications cases of the *mathematical* estimation methods on the present *HE* according to the availability of the *parameter measurements*. *First,* when all the measurement of the four, *inlet* and *outlet, temperatures,* and *MFRs* are *available,* as in the case of the current *HE* at *LENA reactor*. In this condition, all the methods can be applied. *Second,* when some *measurements* of parameters are not available. In this case, the *HB* and the *LMTD* methods can't be used, only the ε-*NTU* and the *KF* methods can be applied according to the available parameters. *Finally*, the application conditions of the *CM* depend on those of the individual estimation approaches used in the combination.

In this monitoring application, we mention that the use of the three mathematical methods, *HB*, ε-*NTU* and *LMTD* needs a *pre-calibration* which consists to find: the *thermal power ratio, R,* between the hot and cold fluids given by *Equation I.17*, the *effectiveness* at both fluids of the *HE* given by *Equations I.26a* and *b*, and the coefficient F_cUA from *Equation I.24* after correction. For this computation, we used an independent *data set,* different of that used for estimation *(Figures V.1* and *V.2*) but with the same values of the *MFRs*. The calculation of these *three calibration values* of the *HE* are represented on the following *figures* (*Figures V.4 - V.6*).

After stabilization (*i.e.,* time k = 1000s), these values are relatively constant: R =1.49, ε_h = 0.61, ε_c = 0.41 and $F_rUA = 4.2\times10^{-5}$.

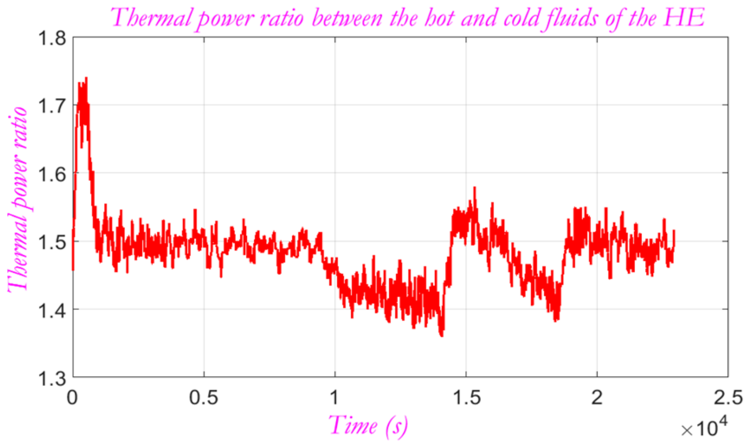


Figure V.4 - Thermal power ratio, R, *between the hot and cold fluids of the HE.*

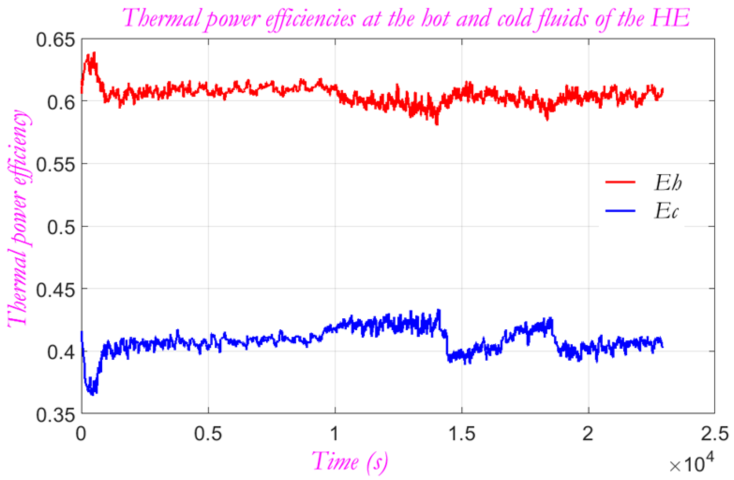


Figure V.5 - Efficiencies, Eh *(εh) and* Ec *(ε_c), respectively, at the hot and cold fluids of the HE.*

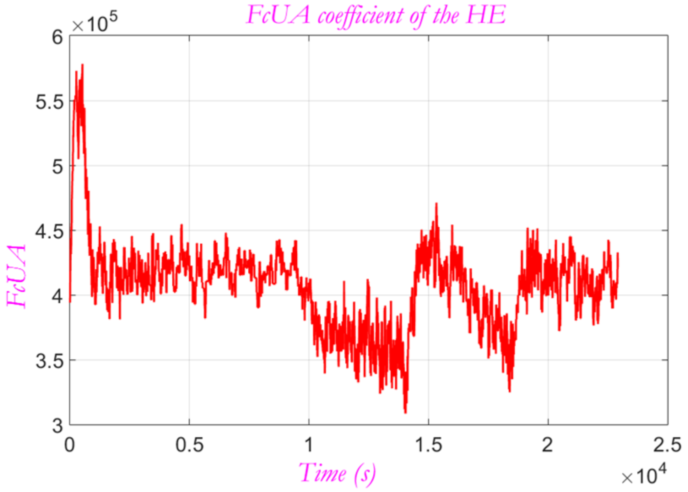
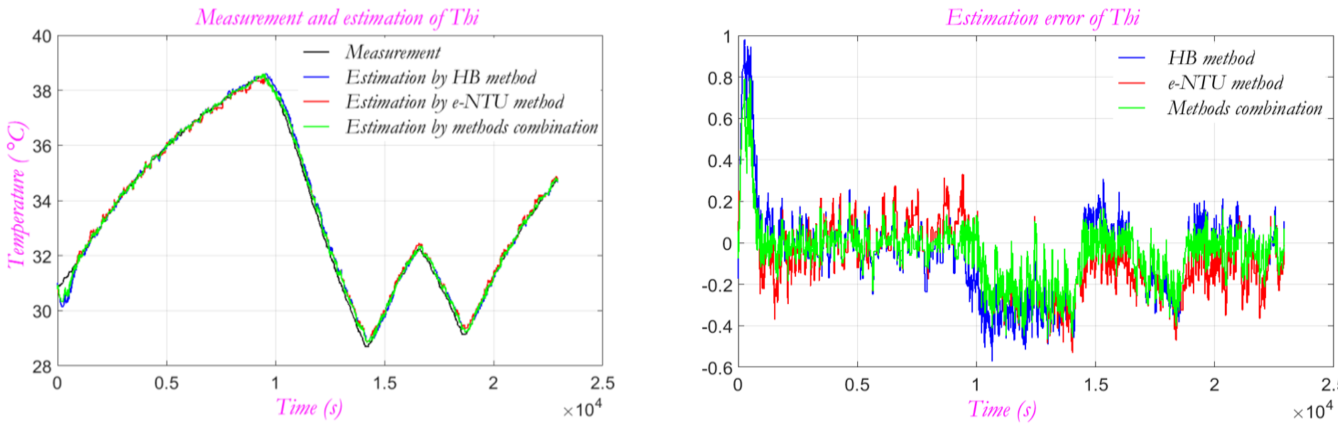
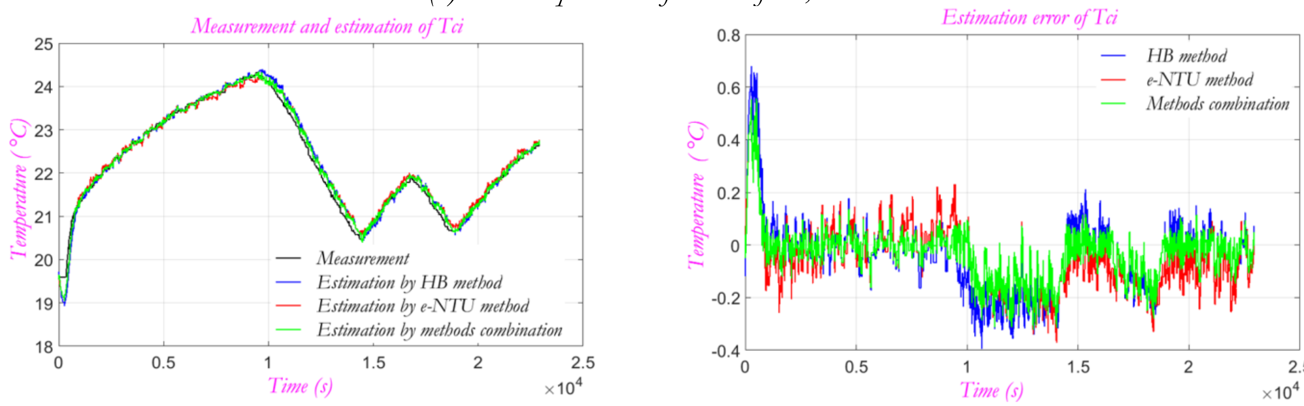


Figure V.6 - FcUA coefficient of the HE.

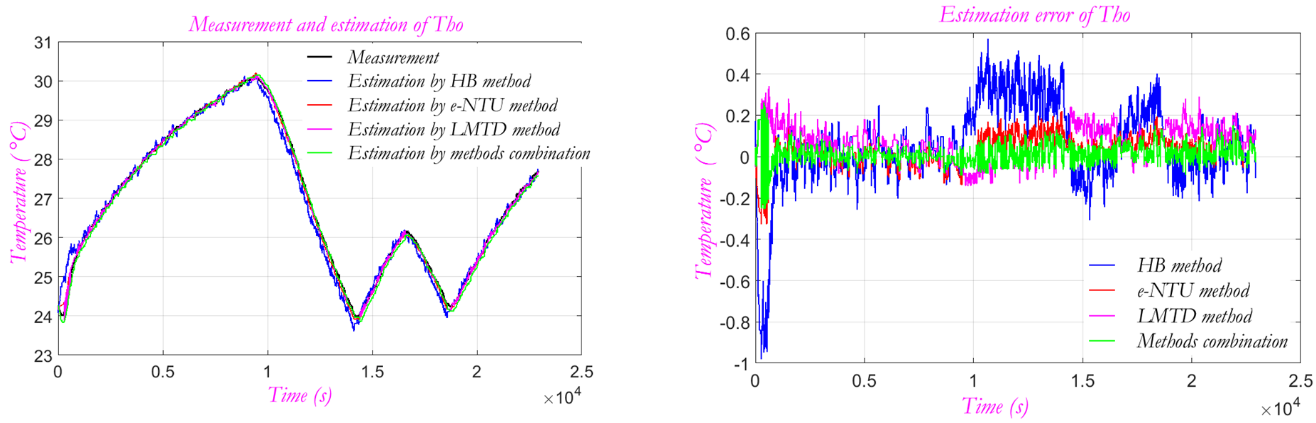
The *estimation* results of the *inlet* and *outlet temperatures*, the *MFRs* and their corresponding estimation errors at both fluids of the *HE* are presented on *Figures V.7* and *V.8*.



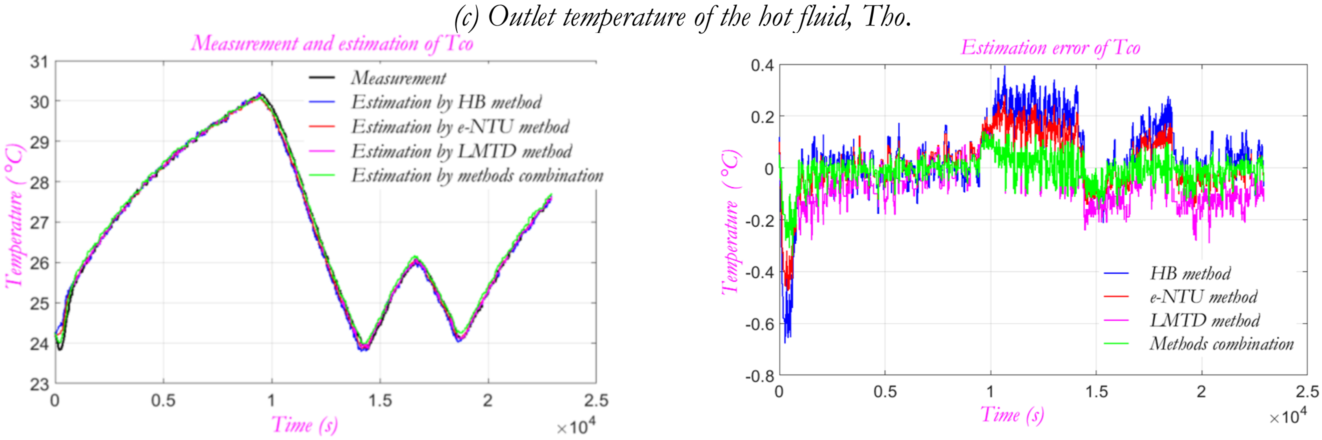
(a) Inlet temperature of the hot fluid, Thi.



(b) Inlet temperature of the cold fluid, Tci.

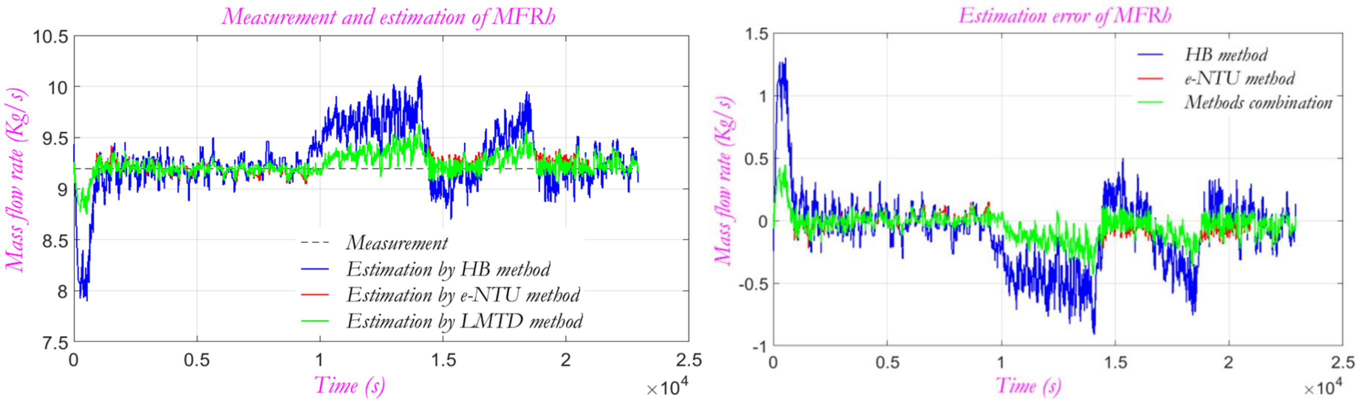


(c) Outlet temperature of the hot fluid, Tho.

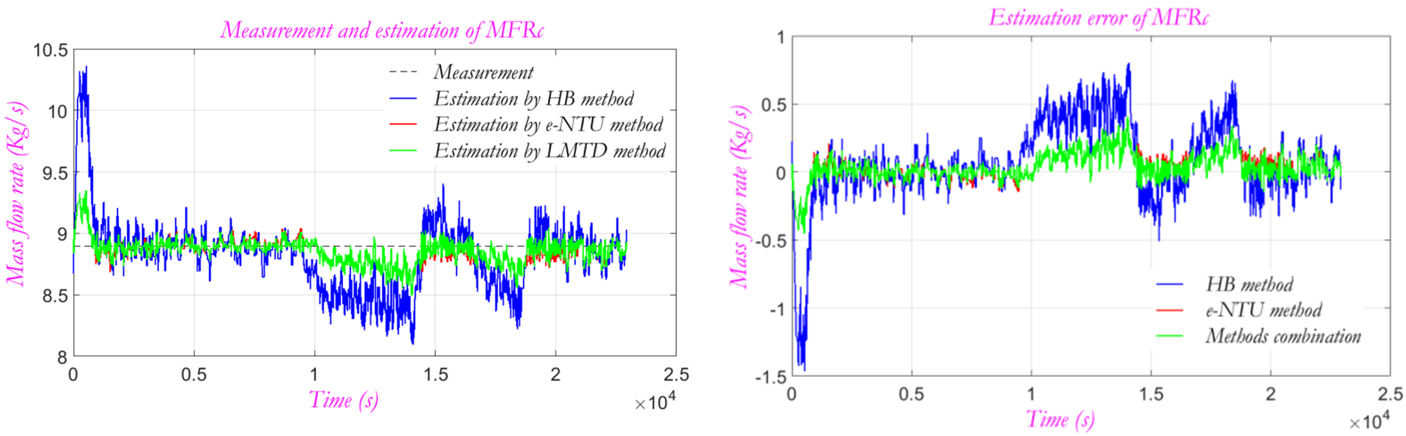


(d) Outlet temperature of the cold fluid, Tco.

Figure V.7 - (Left) Measurement and estimation of temperatures at both fluids of the HE by using mathematical methods. *(Right) Estimation error of these temperatures.*



(a) MFR of the hot fluid, $\dot{m}h$.



(b) MFR of the cold fluid, $\dot{m}c$.

Figure V.8 - (Left) Measurement and estimation of MFRs at both fluids of the HE by using mathematical methods. (Right) Estimation error of these MFRs.

V.2.1.2 - Kalman Filter

The *KF* is suitable to predict the *outlet temperatures* of the cold and hot fluid streams in a specified *HE*. The internal coefficient and some parameters values of the *HE* are given in *Table V.1.* The estimation results of *Tho* and *Tco* and their estimation errors, by using the *KF* are presented, consecutively, on *Figures V.9a* and *V.9b.*

Symbol	Value	Symbol	Value
Vh	131×10^{-3} [m^3]	*ρh, ρc*	993.94 [kg/m^3]
Vc	390×10^{-3} [m^3]	*A*	30,7 [m^2]
cph, cpc	4187 [$J/(kg.K)$]	*U*	1080,80 [$W/m^2\,°C$]

Table V.1 - Coefficient values of the used HE.

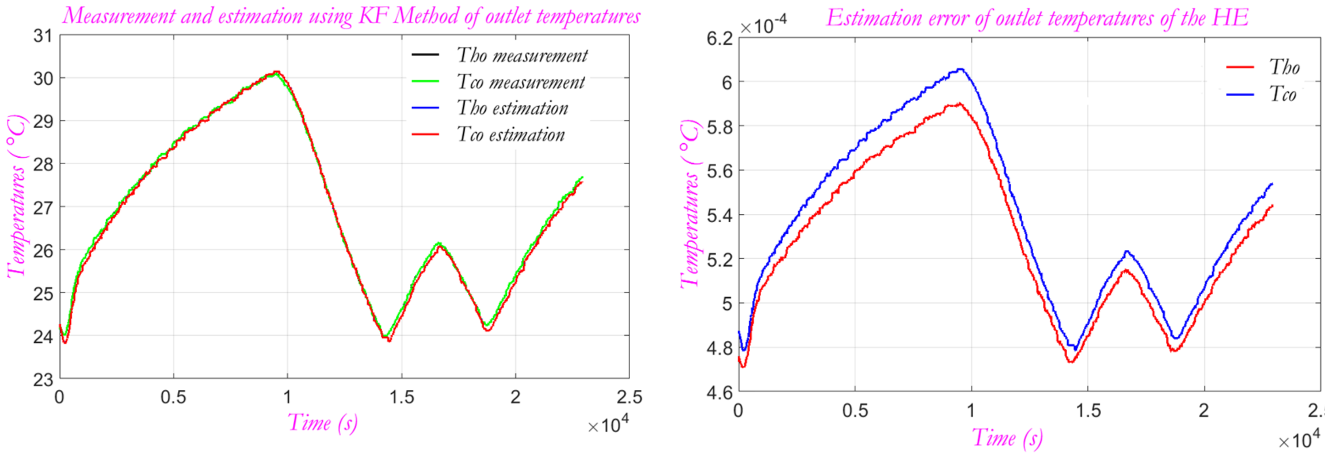


Figure V.9 – (Left) Measurement and estimation of outlet temperatures, Tho and Tco, of the HE by using KF. (Right) Estimation error of the outlet temperatures.

V.2.1.3 - Evaluation of Results

Based on *Figures V.7* and *V.8* at the steady state (*i.e.,* after k =1000s), the four previous errors of the estimation by using *mathematical approaches* and their combination of the *inlet* and *outlet temperatures* of both *streams* of the *HE* are calculated and presented on *Table V.2*. These errors are represented by two values: one for the *Power Up* (*Pu*) and the other for the *Power Down* (*Pd*).

By using the methods combination approach, the percentage composition of the estimation spectrum, function of the selected optimal estimation from the used mathematical methods is, respectively: (51.4, 48.6, 0), (19.6, 47.8, 32.6), (51.9, 48.1, 0), (28.4, 33.8, 37.8), (22.8, 77.2, 0) and (22.7, 77.3, 0) for the six supervised *HE* parameters (*i.e., Thi*, *Tho*, *Tci*, *Tco*, $\dot{m}_h$ and $\dot{m}_c$) as shown on *Figure V.10*.

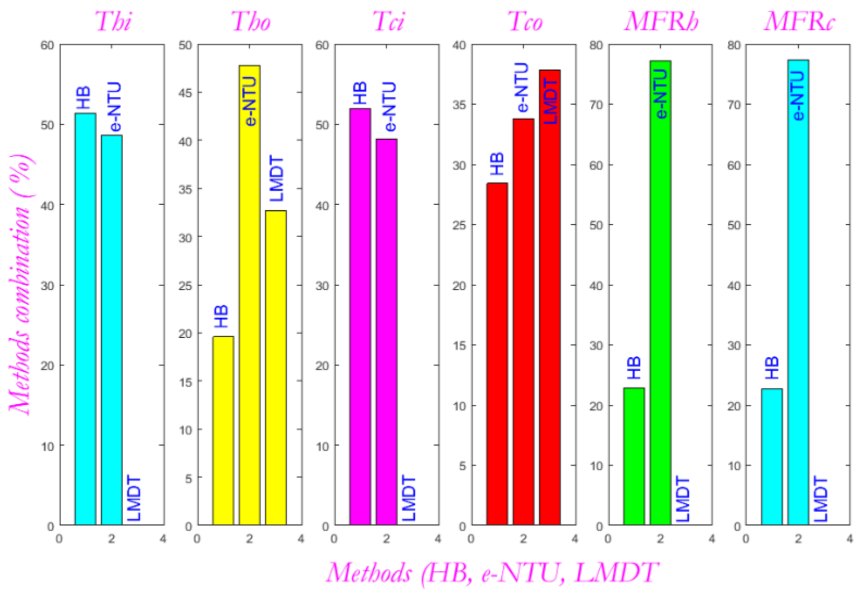


Figure V.10 - Percentage (%) composition of the combination estimation spectrum function of the used mathematical methods.

We not that the estimation is better during the *Pu* for all mathematical methods. The methods combination approach is more accurate because it takes the best of previous approach regarding the estimation. Thus, we can class the used mathematical methods against their estimation accuracy as follow: the methods combination, the *LMTD,* the *ε-NTU* and the *HB.* For the *estimation* by the *KF*, the *MAE*, *Percent Maximum Absolute Error (MAE (%))* and *RMSE,* of the *outlet* temperatures are calculated *over the entire spectrum, Pa*. We note that the estimation accuracy is the best even during the transition period (*i.e.,* just after the starting of the cold fluid *pump*) thing which has not realized elsewhere.

Globally we can say that these results are satisfactory which allowed generating residual with a good accuracy and consequently a better sensitivity of *FDe*.

			Temperatures (°C)				*MFRs (kg/s)*	
Errors	*Methods*	*Or*	*Thi*	*Tho*	*Tci*	*Tco*	$\dot{m}h$	$\dot{m}c$
MAE	*HB*	*Pu*	0.306		0.212		0.496	0.508
		Pd	0.572		0.395		0.912	0.803
	ε-NTU	*Pu*	0.368	0.151	0.258	0.165	0.223	0.211
		Pd	0.532	0.219	0.372	0.282	0.437	0.404
	LMTD	*Pu*		0.290		0.290		
		Pd		0.240		0.240		
	Comb.	*Pu*	0.232	0.150	0.162	0.160	0.223	0.210
		Pd	0.464	0.150	0.321	0.140	0.437	0.404
	KF	*Pa*		0.59 *m*		0.60*m*		
MAE (%)	*HB*	*Pu*	0.999	1.227	1.00	0.853	5.399	5.708
		Pd	1.597	1.966	1.674	1.358	9.917	9.023
	ε-NTU	*Pu*	1.131	0.663	1.189	0.663	2.425	2.367
		Pd	1.842	0.969	1.800	0.969	4.757	4.541
	LMTD	*Pu*		1.124		1.137		
		Pd		0.996		1.006		
	Comb.	*Pu*	0.676	0.555	0.693	1.137	8.421	2.364
		Pd	1.576	0.608	1.524	1.006	4.757	4.541
	KF	*Pa*		0.002		0.002		
RMSE	*HB*	*Pu*	0.078		0.054		0.098	0.095
		Pd	0.236		0.163		0.357	0.326
	ε-NTU	*Pu*	0.110	0.045	0.077	0.046	0.063	0.060
		Pd	0.187	0.077	0.131	0.118	0.124	0.117
	LMTD	*Pu*		0.077		0.093		
		Pd		0.131		0.052		
	Comb.	*Pu*	0.058		0.040	0.033	0.051	0.049
		Pd	0.176		0.123	0.047	0.123	0.157
	KF	*Pa*		0.53*m*		0.54*m*		

Table V.2 - Presentation of the estimation errors: the MAE, MAE (%) and RMSE. They are calculated after the time k=1000s (i.e., transition period) for the HB, e-NTU, LMTD and CM; and over the entire spectrum for the KF methods. In this table we used the following notation : Milli or 10^{-3}(m), Operating Regime (Or), Pu, Pd and All Power Regimes (Pa).

V.2.2 - Neural Networks for Estimation of HE and Core Parameters

In this part of experience, *NN* is applied to model the *HE* and the *core* to validate *signals* of the different *parameters* and to accommodate them in the case of faults, by using experimental data. In order to better do that, it is necessary to select the right structure which train correctly the network with the appropriate data, and predict accurately the network outputs.

In our application, *seven* prototype *parameters* of the reactor in *two* different *systems* are selected to be *monitored*. The *Nuclear Power* (*Pn*), *Tf* and *ρ* in the *core*; and the *inlet* and *outlet temperatures* of both streams of the *HE* of the *primary cooling circuit* of *Triga Mark II NRR*. So, the major scope of this experimental part is to develop a *NN* model to *predict* these different *parameters*.

We based on the use of a smaller number of input variables of *NNs* which permit to realize a faster training time.
The *number* of *hidden layer* and *neurons* inside (*hidden neurons*) was changed several times and the training parameters were varied; and the error from the network in all cases was investigated. The optimum *NN* architectures were established by choosing the configuration that obtained the minimum prediction error and highest *CC*.
In order to obtain a suitable structure, several architectures are used and several configurations for each architecture were tested then optimized through trial and error procedure. As a result of these tests for this monitoring application, *NARX* structure is selected owing to its best performance to estimate the dynamic of signals.
Furthermore, the optimum number of the hidden layer was found to be one and the optimum number of neurons of the hidden layer was found to be *six*. *(Hornik, 1989; Baughman, Liu, 1995)* mention that networks with one hidden layer can show their ability to estimate the value with a sufficient degree of freedom as well as effectively identifying process faults or feature classification.
The number of nodes in the input layer is set to be equal to that of the input signals in each system and the output layer has only one node from which the output is predicted.
The connection weights were randomly assigned in the initial learning stage; then they were adjusted after every learning epoch using the backpropagation learning rule.
Using three activation functions, hyperbolic tangent (*sigmoid function*), linear and sigmoid functions, we found that the last one is more suitable to predict network outputs.

The samples for training test and validation are collected from *measurement channels* and *data acquisition* (*Data Acquisition Supervision PC*) at *LENA Reactor* for *fault-free* (*i.e., healthy*) *systems*.
All input and output data are normalized to the range from 0 to 1.
In this experiment, the data set of the *three core signals; Pn*, *Tf* and ρ *(Figures V.12a* and *b*); and the *four inlets* and *outlet temperature* of the *HE (Figure V.14*) to be *monitored* was divided into three subsets with approximately 70% for training, 10% for validation, and 20% for test.
Error signals were arbitrarily simulated by adding or subtracting supplement values to or from the normal graph.

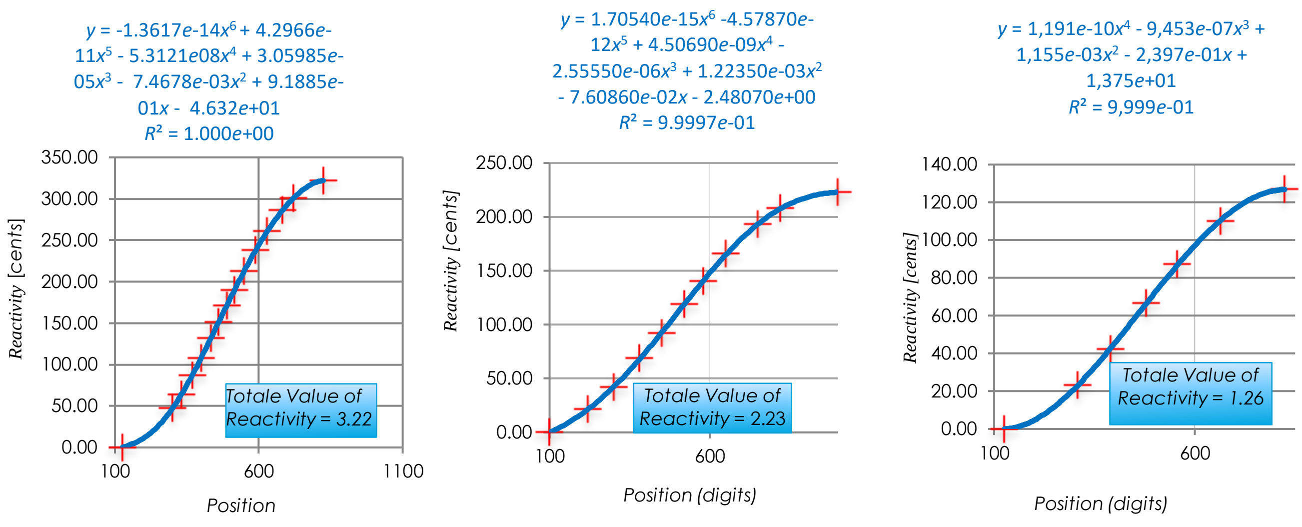
The *NN* model is trained using several algorithms with early stopping to avoid over-fitting. Training of the network is done several times until a *maximum CC* for the validation data occurs. The *Levenberg-Marquardt* (*LM*) routine often finds better optimal solution for a variety of problems as compared to other optimization methods. Its error decreases much more rapidly with time than the other algorithms.

After the training of *NN* with a large number of offline data*,* the dynamics of the *healthy systems* is learned and the knowledge about the system dynamics and mapping characteristics are implicitly stored within the networks. Then the *NN* is used as a reference model to compare it with the output of the actual system and to generate the residual signal. This residual would act as a fault signature, since when a fault occurs in the system the magnitude of the residual increases.
In this experiment we are interested by the *maximum error of prediction*, *mean value* and *RMSE*, over all the reactor mode of operation (*i.e., start-up*, *nominal* and *shoot-down*). Indeed, these values are used for the choice of the threshold value of the alarm activation. So, our goal is to get the lowest value of this quantity to have the best sensitivity possible for the *FDe*.

V.2.2.1 - Estimation of Core Parameters

For the ρ measurement, all the *three control rods* were calibrated in dependence on the *rod position* by the *positive period method*. This method consists of *withdrawing* the control rod from a known critical *position* through a *small distance*, and then to *measure* the stable period of the resultant reactor transient. The period was obtained using the doubling time that is the time required for the power, given by *Equation I.2*, to increase by a factor of two. The experimental integral worth curves relative to these *three control rods* (*i.e., shim, regulation* and *safety*) are respectively given on *Figures V.11a - c*.

The total ρ in the core is calculated by adding the resulting ρ's of the move of each rod (*SHIM* and *REG*). We suppose that the *safety control rode* is not used (*out of service*).



(a) (b) (b)

Figure V.11- Experimental integral control rod worth curve: (a) shim, (b) regulating and (c) safety.

For the *core* we used tree similar *networks* to estimate individually *Pn, Tf* and *Rho*. For the estimation of *Pn*, we used *Tf* and *Rho* as inputs, individually and together to compare the different accuracy results. For the estimation of *Tf* and *Rho*, we used *Pn* as a single input.

The *number* of *input* nodes is equal to the number of input variables (in this part of experiment, the number of input variable is *one* or *two*). The *output nodes* form the *output layer* and their *number* is linked to that of *signals* or *parameters* to be *monitored*.

The three-experimental data set, *Pn,* the *Tf* and ρ of the *core* to be monitored at *LENA Reactor* are shown on *Figures V.12*a and *b*.

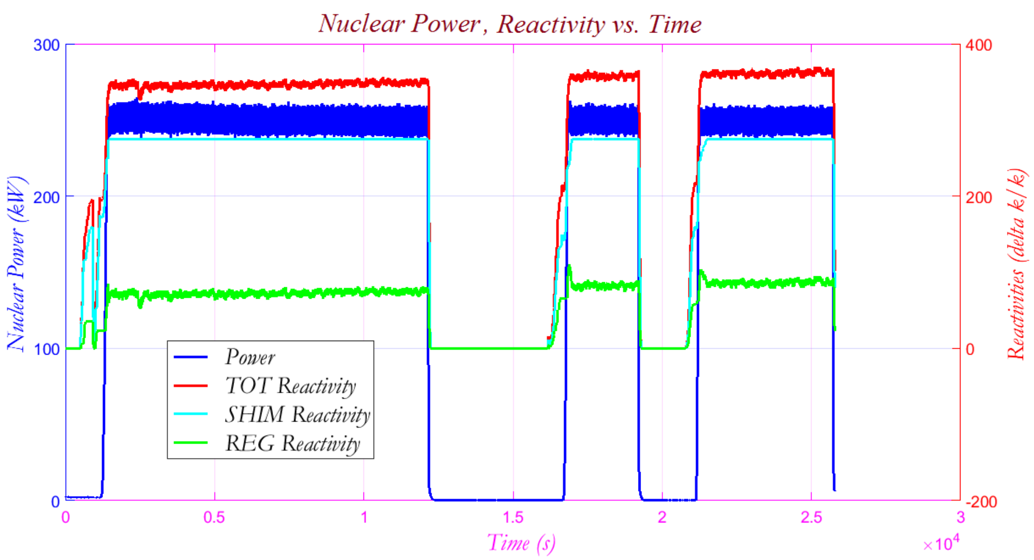


Figure V.12a -Data set of Pn and ρ in the core.

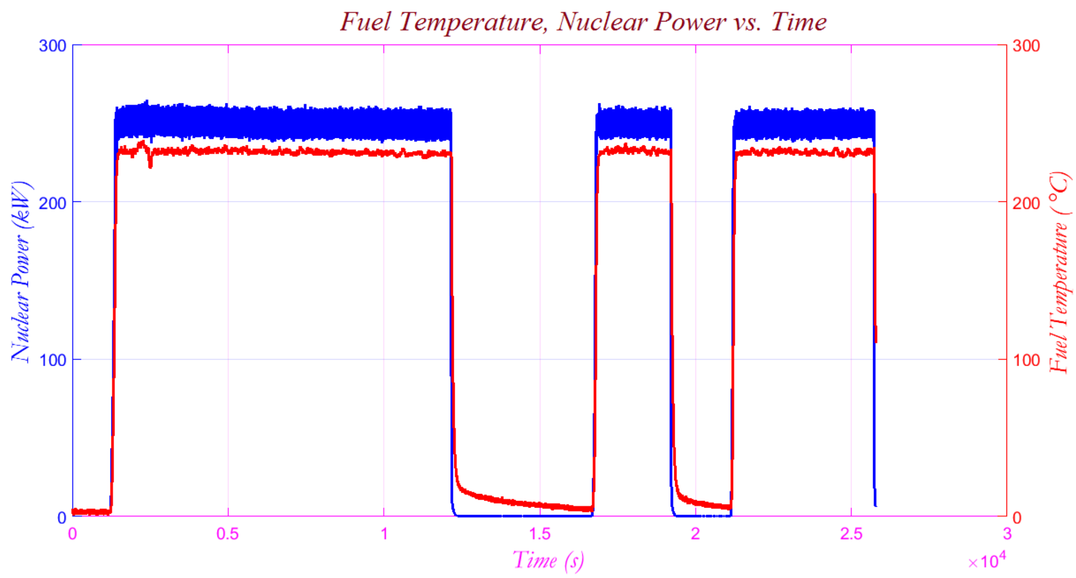
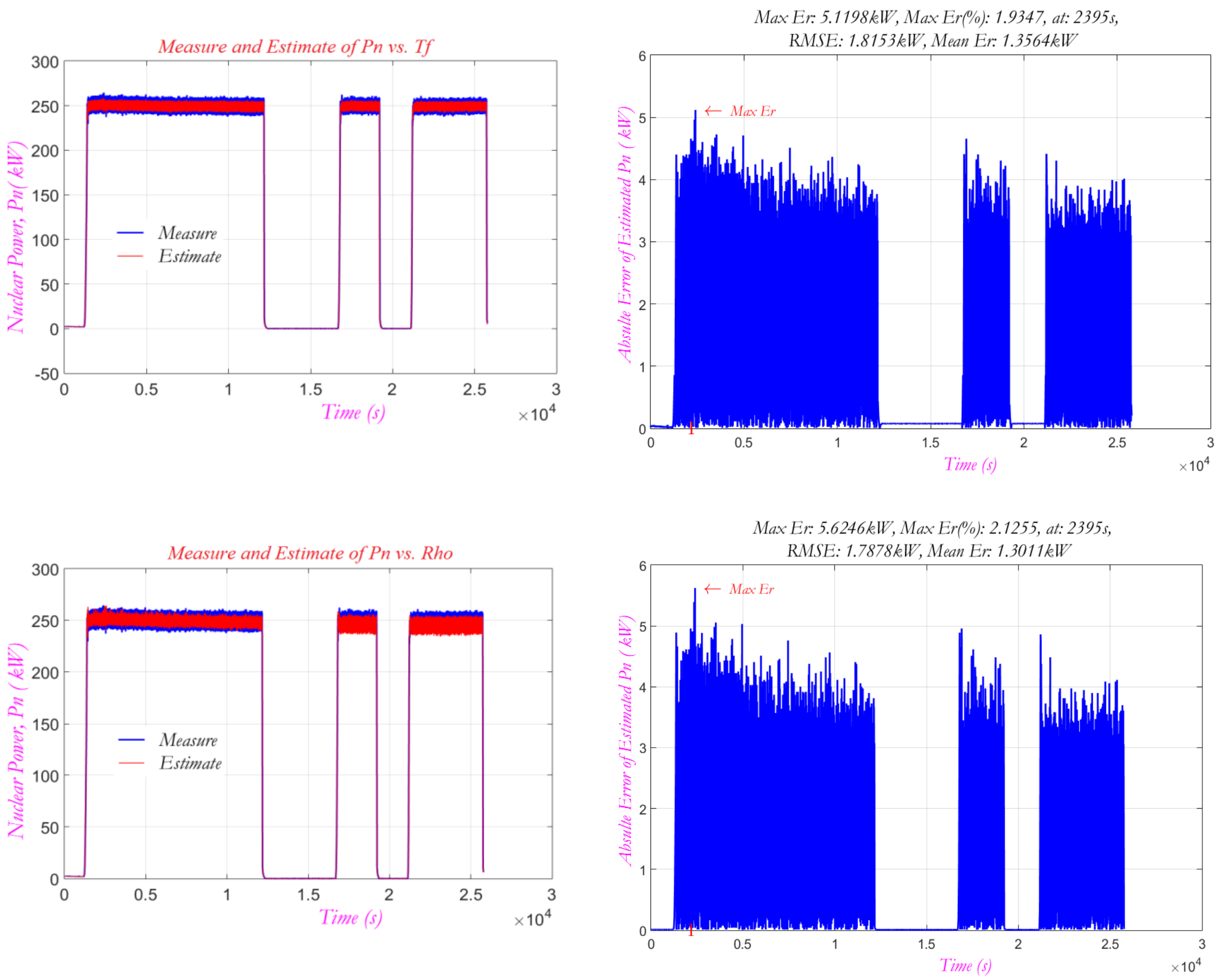
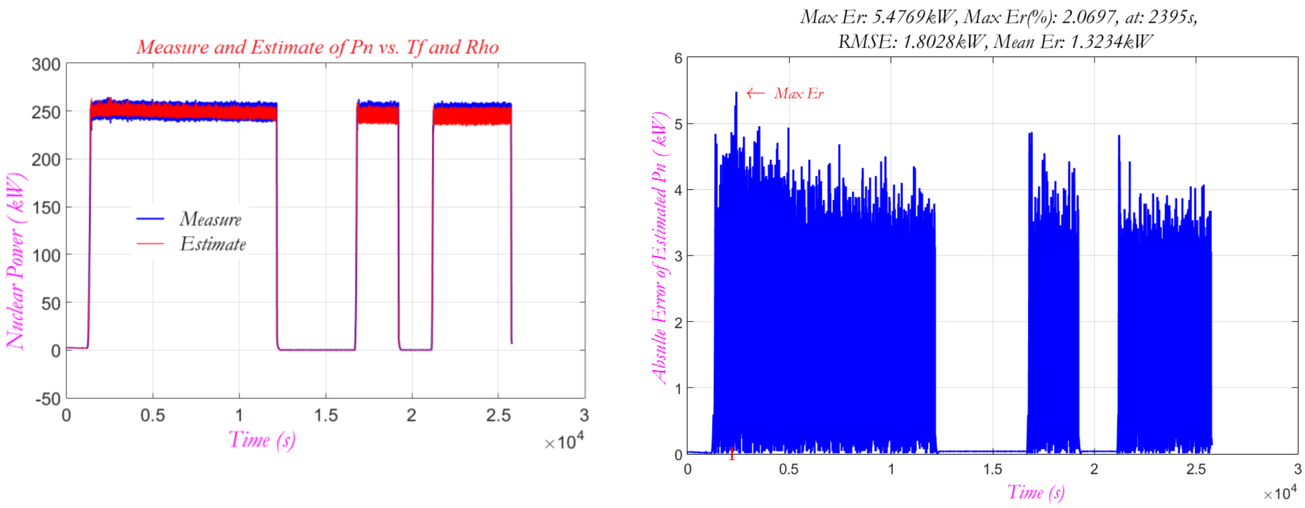


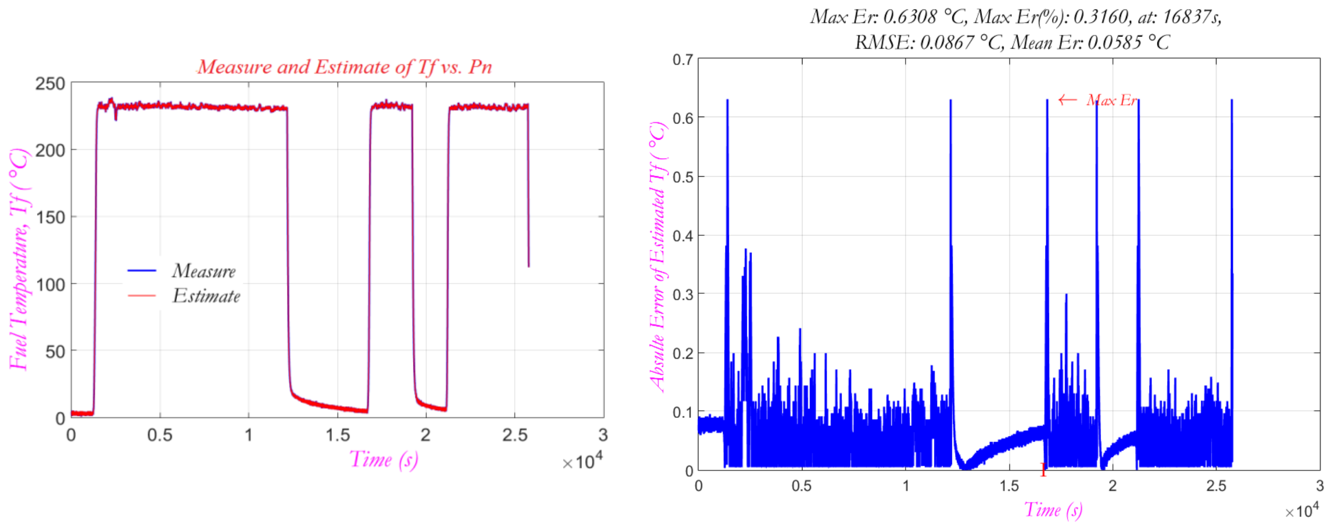
Figure V.12b - Data set of Pn and Tf in the core.

The observed minimum *RMSE*, *ME* (%) and *MeE* for every estimated output parameter are mentioned on *Figure V.13*. This *Figure* shows that three principal manners are used for the prediction of the *Pn* by using *Tf* and ρ *independently* and *together*. We not that the errors of these prediction manners are almost the same, but still the prediction of *Pn* is better when we use ρ alone as input for the network-based estimator which gives a *stable* and *minimum error* over all operation modes of the reactor.

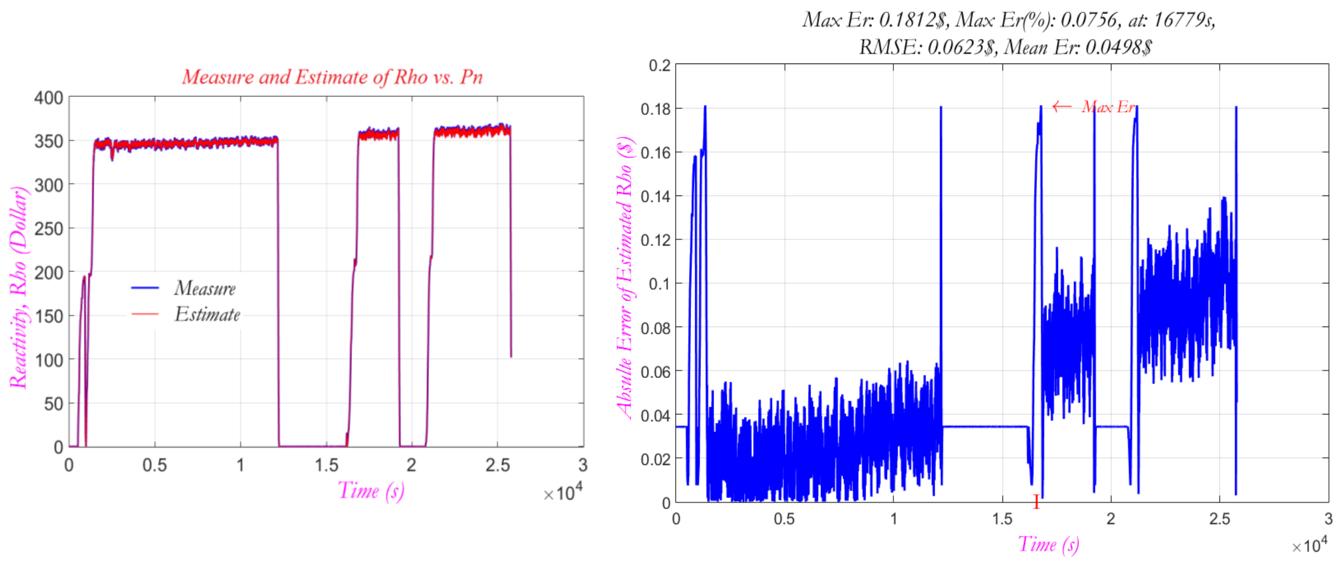




(a) Pn of the Core.



(b) Tf of the Core.



(c) ρ of the Core.

Figure V.13 - (Left) - Measurement and estimation of outlet temperatures, Pn, ρ and Tf. (Right) - Absolute error of the estimated parameters.

The estimations of *Tf* and ρ are presented respectively on *Figures V.13b* and *c.* We note that the estimation error is *high* at the *transition* (*i.e.,* the *start-up* and *shoot-down*) *regime*. Furthermore, we can also predict the *Tf* by using ρ alone or with *Pn* as input to the network-based estimator and the same thing for the estimation of the ρ by using *Tf* and *Pn as inputs*.

V.2.2.2 - Estimation of Heat Exchanger Parameters

For the *HE* we used four similar *networks* to estimate individually *inlet* and *outlet temperatures* of the *hot* and *cold streams.* The *input* variables for each *network* model are both the two *outlets* and *inlet temperatures measurements* except that to be estimated.

Each network model has one input layer with three nodes which equal to the number of input variables and the number of neurons in the output layer is equal to one.

The *four-experimental data sets* of *inlet* and *outlet temperature* of the *HE* are shown on *Figure V.14.* The prediction of these *temperatures* is given on *Figure V.15.*

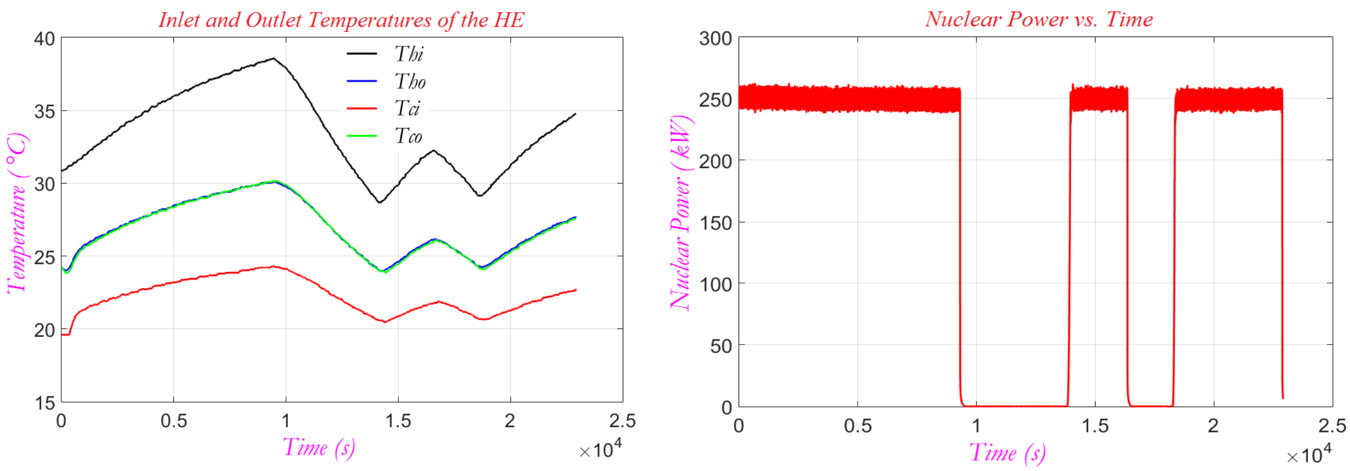
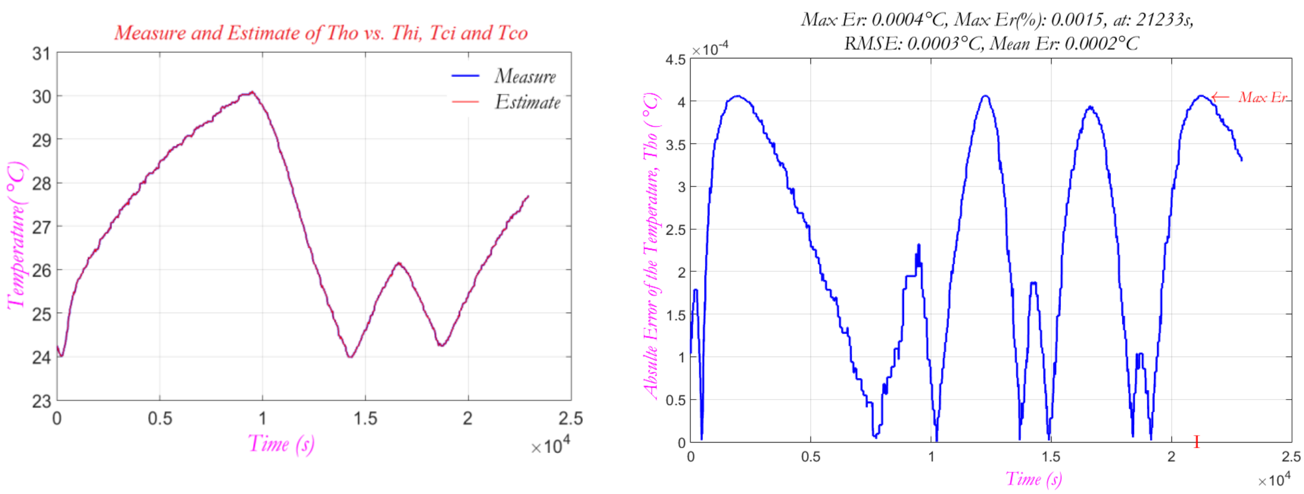


Figure V.14 - (Left) Data set used for the prediction of inlets and outlets of the HE. (Right) The corresponding Pn.



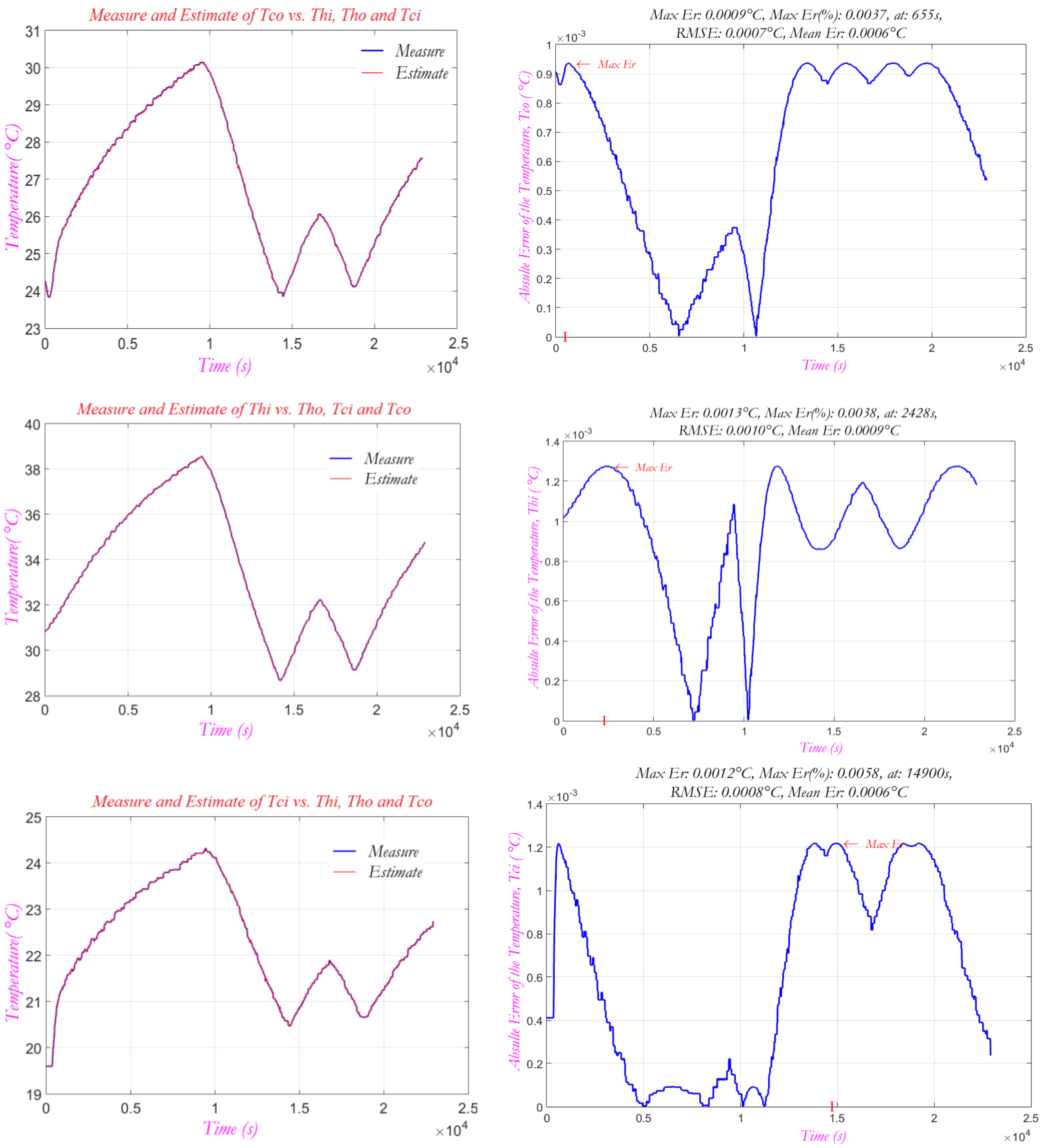


Figure V.15 - (Left) estimation by NNs of one among four, inlets and outlets, temperatures of the HE vs. other temperatures. (Right) Absolute error of the estimated temperature.

V.3 - Fault Accommodation

To be able to detect and locate several possibly faults and accommodate them, there are several well-established schemes, proposed in the literature, which are specifically designed to manipulate multiple sensor faults. These include the using of the *observers bank*, so-called *DOS* and *GOS* *(Frank, 1990)*, bank of the *KFs* *(Kobayashi, Simon, 2003; Xue, Guo, 2010)*, *Interacting Multiple Model* (*IMM*) *(Zhang, Rong, 1998; Hwang et al., 2010)* and *MMKF* *(Hanlon, Maybeck, 2000)* and *NNs* based *SA* *(Samy et al., 2011)*.

The general structure represented on *Figure V.16* is indicated to detect, isolate and accommodate multiple faults fast and accurately, in sensors. It uses a bank of estimators, *Ej*, where the subscript *j* takes values from 1 to *m*, with m is the number of parameters to be monitored.

Each estimator E_j is designed for detecting a specific *parameter* fault. It is excited by all input parameters (supposed non-faulty) except that to be estimated, P_j.

The difference in absolute error, AE_j, between the measurement of the parameter to be monitored, $P_j(k)$ and its estimation, $\hat{P}_j(k)$, is made by Da_j. The result, present the residuals, is compared at a *logic compactor,* C_j, with a prefixed maximum tolerated *error threshold, Thj*. When any of the parameters is not faulty, their measurements are forwarded to the outputs. In the opposite case when one parameter, P_i, is faulty, the residual exceed a prefixed maximum tolerated error *Thi*, the output of the comparator C_j which represents the residual $R_j(k)$, jumps from 0 logic to 1, then the parameter P_j will be declared faulty and the estimation, $\hat{P}_j(k)$, takes place as *FAc* or *fault recovery* on the output $\tilde{P}_j$ via the switch S_j (*controlled* by the output of the comparator C_j). So, by checking properly *residuals*, R_1, R_2 … R_m, multiple faults can be detected, isolated and reconciled by using this scheme.

By waiting for the intervention of maintenance and calibration teams, this solution can be used occasionally for control, for display to plant operators, or for other critical tasks and therefore, the plant could continue operating without interruption (by supposing that other parameters are not degraded).

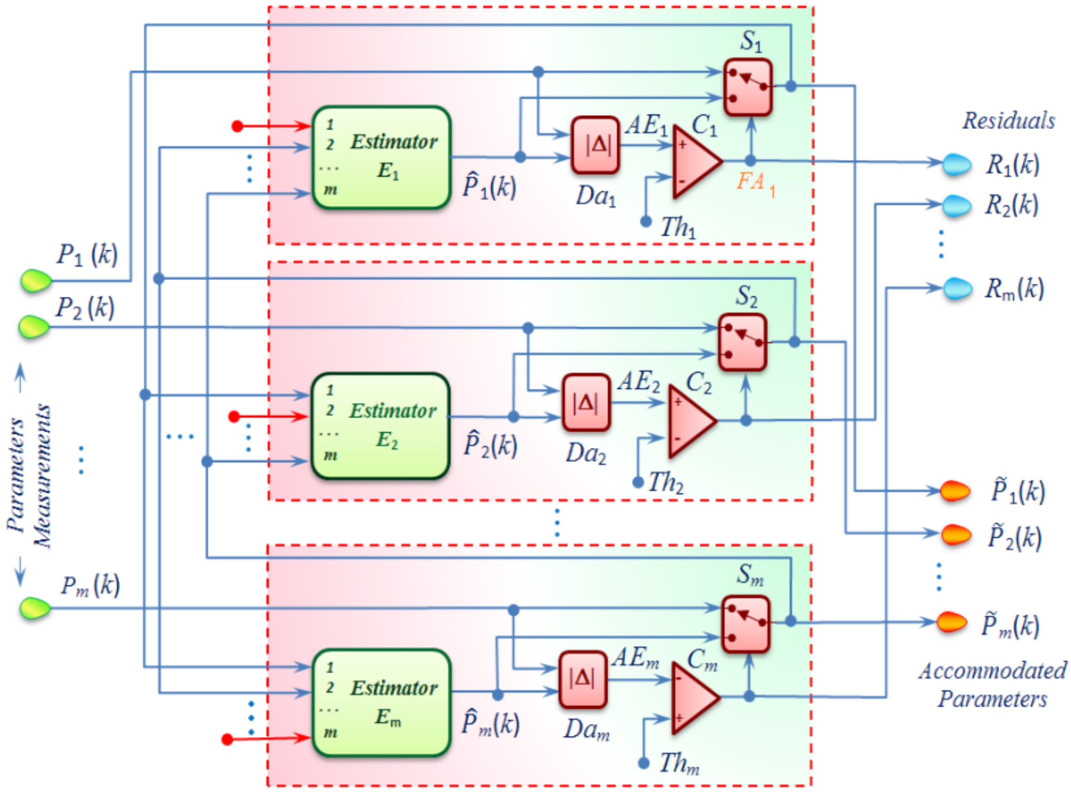


Figure V.16 - Bloc diagram of the FDe, isolation and accommodation system of m parameters.

We not on *Figure V.16* that we have used the output $\hat{P}_j$, provided by the estimator E_j for both the *FDe* and the *FA* of the parameter P_j. Unfortunately, some estimators cannot do both. As the *KF* which is considered as a perfect tool for *FDe* in *LSs*, but in the case of fault, it cannot ensure *accommodation* task because its *output prediction*, given by *Equation I.46*, depends on the *a posterior state*, $\hat{x}_k^+$, which in turn depend on the *present input measurement,* as appears consecutively in *Equations I.37* and *I.41*. Therefore, in this case, we need to use a second estimator for *FA* as shown on *Figure V.17*.

V.3.1 - Mathematical Models

Figure V.17 is the result of applying the *accommodation* scheme presented on *Figure V.16* with six *input* parameters: *Thi*, *Tho*, *Tci*, *Tco*, $\dot{m}_h$ and $\dot{m}_c$, and six output parameters to be accommodated: $\tilde{T}hi$, $\tilde{T}ho$, $\tilde{T}ci$, $\tilde{T}co$, $\tilde{\dot{m}}_h$ and $\tilde{\dot{m}}_c$.

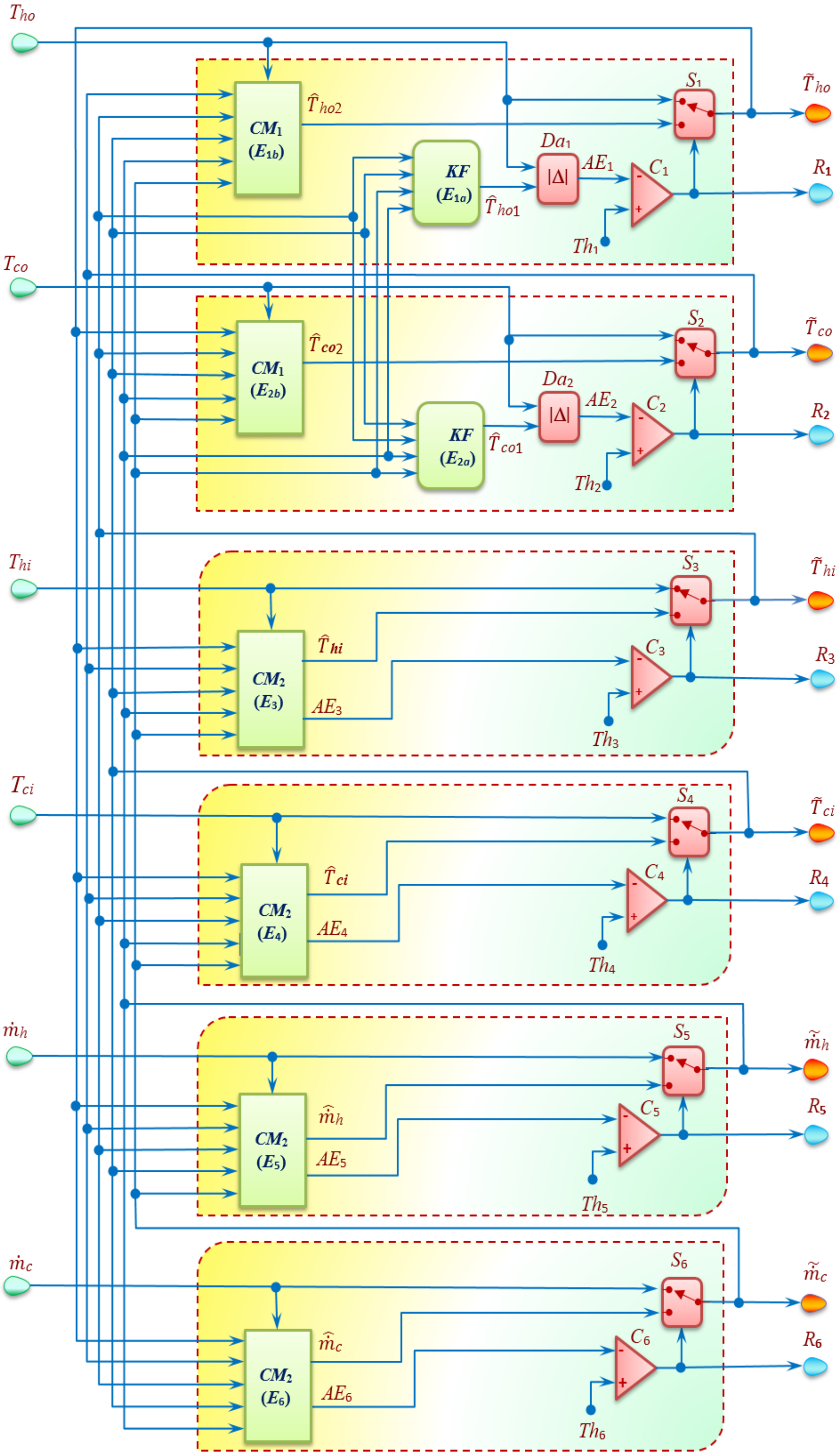


Figure V.17 - Scheme of FDIA of the HE parameters.

Due to their high estimation accuracy, two *KFs* are used as E_{1a} and E_{2a}, which provide the estimations $\hat{T}ho_1$ and $\hat{T}co1$ for *FDe*. Furthermore, a *combination, CM*$_1$, of *HB*, *NTU* and *LMTD* methods are used as E_{1b} and E_{2b}, which provide respectively the estimations $\hat{T}ho_2$ and $\hat{T}co_2$ for *FAc*. The choice of this *methods combination* technic is due to its better estimation capability.
Moreover, a *combination, CM*$_2$, of *HB* and *NTU* methods are used as E_3 - E_6 for both, the *FDA* of parameters: *Thi, Tci,* $\dot{m}_h$ and $\dot{m}_c$, respectively. For each parameter, a residual is generated by comparing the *absolute difference* between the estimation and the measurement generated by Da_1 and Da_2 for *Tho* and *Tco*, and by AE_3 - AE_6 for *Thi, Tci,* $\dot{m}_h$ and $\dot{m}_c$, with the thresholds Th_1 - Th_6 respectively. These thresholds are adjusted slightly above the corresponding *MAEs* to avoid frequent *FAls* due to noise and uncertainties. These thresholds are specific to the used estimation method for each parameter as given in *Table V.2.*

On *Figure V.18*, we simulated on the *Thi* measurement the three types of faults given on *Figure I.4, i.e., abrupt*, *intermittent* and *incipient*, and we presented the supervision result by applying the schematic given on *Figure V.17*. As result, we not that the *FAc* of this parameter, *Thi,* is independent of the shape of the simulated fault but depends only on its amplitude. We note also that this fault simulation can be generalized to the other *HE* parameters and the same remarks on the *FS* will be made.

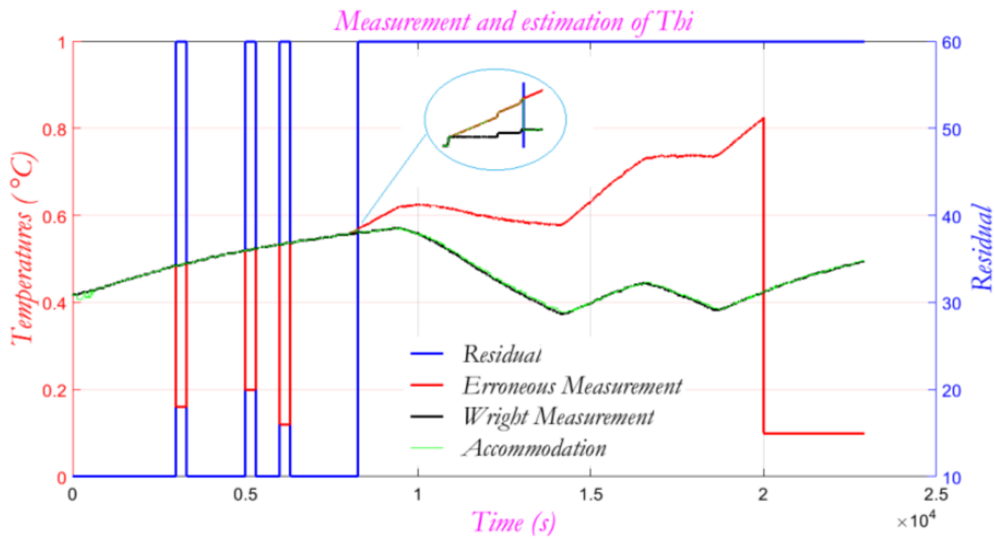


Figure V.18 - FS result with simulation fault of Thi temperature of the HE.

V.3.2 - Neural Networks

In our application, seven parameters P_1 to P_7 are monitored. P_1, P_1 and P_2 are respectively the P_n and the *Tf* at the *core*, and P_4 to P_7 represent the *inlet/outlet temperatures; Tho, Tco, Thi* and *Tci* of the *HE* situated between the primary and secondary cooling loops (*Figure I.1*). So, seven estimators E_1 to E_7, based on the *NNs*, are needed for the *monitoring* and *reconciliation* of these seven parameters respectively.
We used two independent monitoring systems. One for the core and the other for the *HE*. The first one given by *Figures V.19* and *V.20,* receives the P_n and the T_f and the ρ parameters and generates the reconciliation relative to these parameters. The ρ is computed from control roads measurements as given on *Figures V.11a - c,* is used as input for the estimation of the two precedent parameters (P_n and T_f).
The *second* system, given by *Figures V.21* and *V.22*, receives *inlet/outlet temperatures; Tho, Tco, Thi* and *Tci* of the *HE* situated between the primary and secondary cooling loops.
Hence, the *monitoring system* composed of two sub-systems given by *Figures V.20* and *V.22* operates with plant's operational data collected on-line from *ADS of the reactor* every second. Thresholds *Thi* in both *sub-systems* are adjusted to values in concordance of the *maximal error* found in the test part of the network relative to each

parameter to be monitored. If the deviation between measured and estimated values is small enough, the plant is considered to be operated normally. If one of the deviations exceeds the limit, a default is declared. So, the operator can recognize which parameter is abnormal and when the anomaly starts. We can conclude that it has been shown that the proposed monitoring system works satisfactorily in (*RTM*) of the plant conditions of a *TRIGA MARK II Reactor* at *LENA*. Also, this monitoring system is able to *detect*, *locate* and *accommodate anomalies* quickly with a good precision. The drawback of this scheme that it cannot detect more than one faulty parameter at the same time.

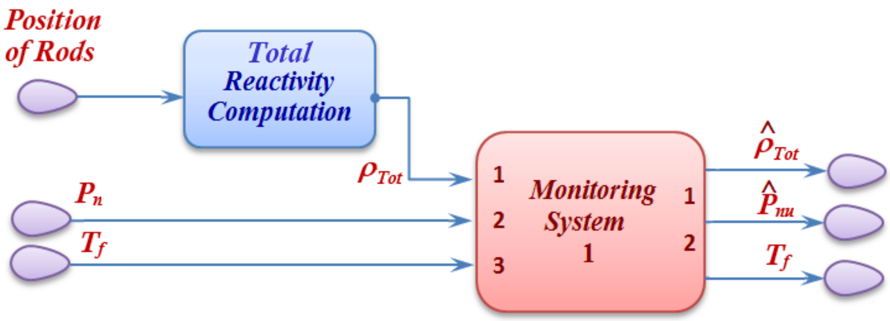


Figure V.19 - Bloc diagram of the supervision system of the Core.

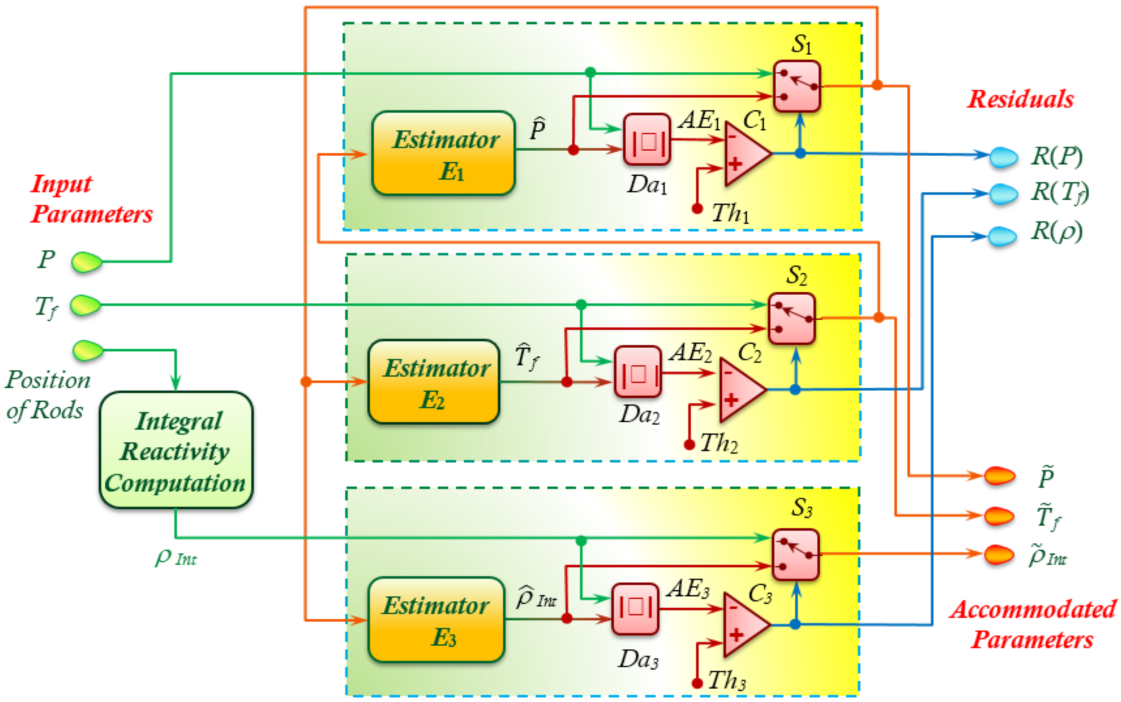


Figure V.20 – Detailed bloc diagram of the supervision system of the Core.

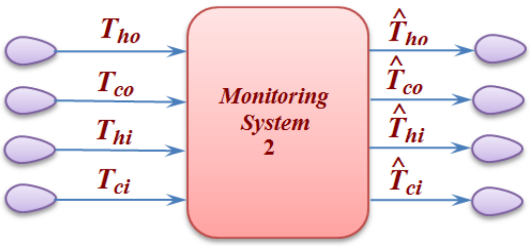


Figure V.21 - Bloc diagram of the supervision system of the HE.

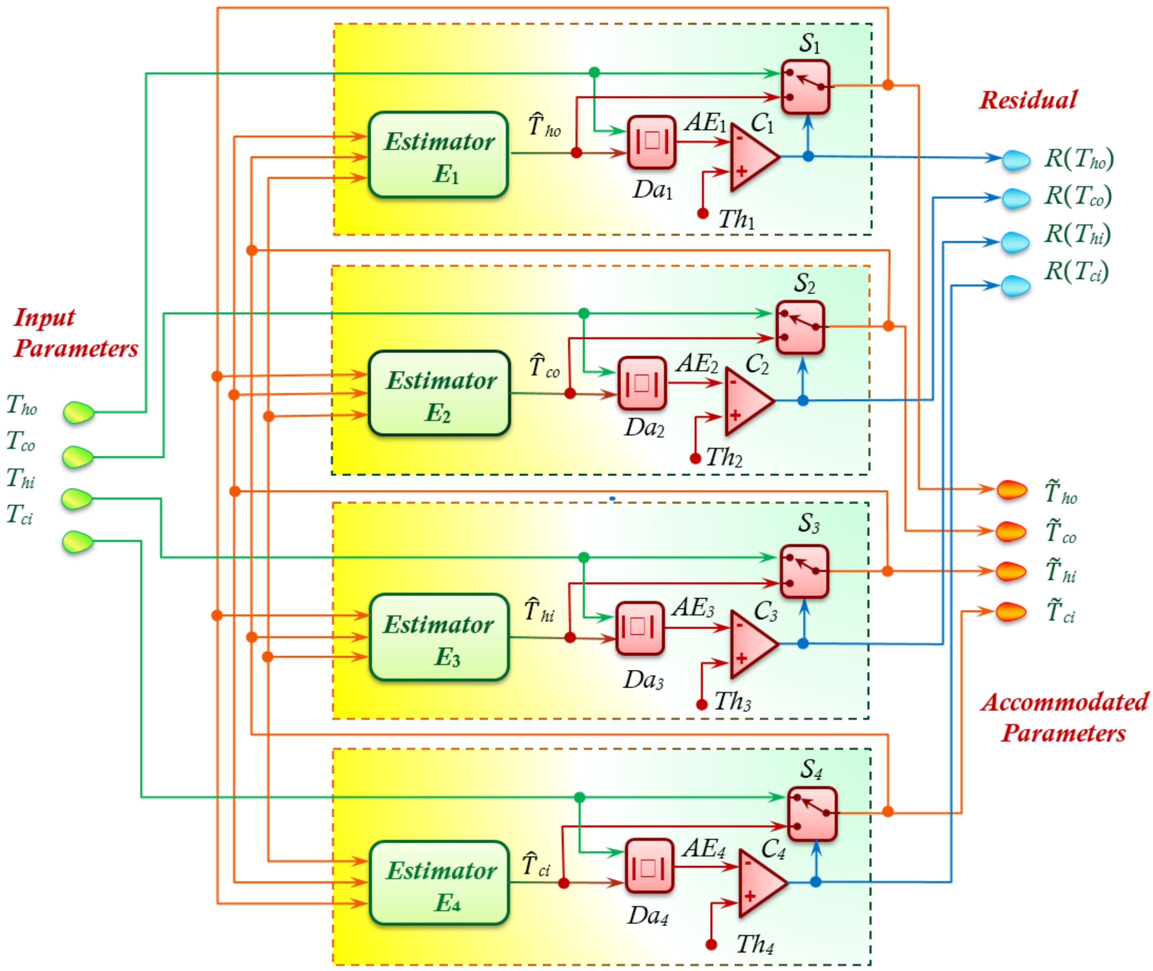


Figure V.22 – Detailed bloc diagram of the supervision system of the HE.

V.4 - Conclusion

In this chapter, we have presented and analyzed the obtained *simulation results* by applying two methods in the automatically *FM* and *FAc* of faults in *NRR* systems, particularly the *HE* and *core*. The first method is based on mathematical method and *KF* used to estimate the hydraulic parameters of the *HE*. The second method is based on *NNs* which is used to estimate the parameters of the *HE* and the core. For the two experiment methods, all the used signals were recorded under real conditions on supervision computer in control room made by data acquisition system in normal operation. For the test, we have introduced a set of consecutive faults of different type on one parameter to be supervised. Finally, we compared the two methods and by appearing their advantages and drawbacks. These approaches can be applied on the other systems of *NRR*. If we have a detailed acknowledge, mathematical methods are preferred, but in the opposite case, *NNs* are recommended. In both cases, the requirement is to have a significant amount of operating data of the system to be monitored. However, if the data are not available, they can be obtained by means of computer simulations with reliable models of the system under study *(Fragkoulis, 2008).*

We conclude that a model with good predictive capabilities can be used as a tool to assess changes during the operating conditions of a system and to check its performances. Finally, we can say that the obtained results are satisfactory for these types of systems.

General Conclusion and Perspectives

This thesis deals with an automatic monitoring (detection and diagnosis) and accommodation of the parameters of the HE and core of a NRR by using two different approaches. The first method is based on *NN*s used to estimate the parameters of the HE and the core. The second method is based on mathematical method (*i.e., HB*, *ε-NTU*, *DTLM* and *CM*) and *KF* used to estimate the hydraulic parameters of the *HE*. The *FMA* system can report the operation state quickly and continuously at any time, in real time, and to present a simplified analysis and results to the operator and assist him in his decision.

Among the supervised parameters in this work, the fuel temperature, reactivity and nuclear power which are the most monitored in the *core* under both steady-state and transient operations. For the *HE*, the mainly supervised thermal-hydraulic parameters are *temperatures* and *MFRs* at both streams. This *HE* is *a shell-and-tube* type in which the *overall heat transfer coefficient, U,* is assumed *temperature independent*, making the *model linear* in the *state representation*. In the opposite case, the model will be *NL* and an *EKF*, *UKF* or other *NL* estimators can be applied.

The results of the two experiment methods (*i.e., analytical* and *NNs*) are presented. All the used signals acquired by data acquisition system were recorded at real time in supervision computer of at control room during normal operation conditions. For the test, we have introduced a set of consecutive faults of different type on one parameter to be supervised. Finally, we compared the two methods according to their advantages and drawbacks. These approaches can be applied on the other systems of *NRR*. If we have a detailed acknowledge, mathematical methods are preferred, otherwise, *NNs* are recommended. In both cases, the requirement is to have a significant amount of operating data of the system to be monitored. However, if the data are not available, they can be obtained by simulations with reliable models of the system under study.

NN, considered as part of *Soft Computing (SC) techniques* has a highly parallel structure and a capability for *storing experiential knowledge* acquired by the networks from its environment through a learning process and making it *available for use*. On the condition of choosing judiciously the neuronal architecture and depending on the completeness and goodness of the learning process, *NN* is considered more interesting solutions for monitoring (*i.e., FDe* and *FDi*) to achieve a higher degree of *fault-tolerance* than conventional tools and, an excellent and efficient *prediction* technique with a good *NL* propriety and, minimization of noise and disturbance. *NN*s have the ability to make intelligent decisions in cases of corrupted data. So, many researchers have perceived *NN* as an alternative way to represent knowledge about the faults.

The strategy of *FMA system* is based on the exploitation of data acquired on the process to be monitored and it is executed in two main steps; the *first* is the development of a reference model of normal state of the parameters to be supervised. For *NNs*, this model is obtained by repetitive off-line training by using historical data, which allow getting a best possible representation by adjusting the network parameters to optimal values. The *second* step realizes the recognizing of the operation state by using the on-line measurement and introduces necessary corrections in case of fault.

The determination of most of the reactor systems parameters is based on the on-line measurements of *S/D* signal. So, monitoring and accommodation of these kinds of parameters is considered as *SeV* operation which permits to monitor the entire trajectory of the signal; from the source, *i.e., S/D,* passing by the associate *measurement chains* (*i.e., data* and *nuclear instrumentation* for *S/D* respectively) and connection till the *supervision* *computer* at the control room. If the signal is not correct, we would like to be able to distinguish between a faulty sensor and a faulty condition of the process being measured.

Finally, we can conclude that from the off-line results, it has been shown that the proposed monitoring system works satisfactorily in real-time monitoring of the *NRR* plant conditions. This monitoring system detects anomalies at the early stage and gives operators a sufficient time to deal with them for the avoidance of reactor shutdowns. Through the integration of *FDe*, *FDi*, and control strategies, good predictive capabilities can be used as a tool to assess changes during the operating conditions of a system and to check its performances. Therefore, this automatic monitoring and accommodation system is considered as potential earnings for a reactor: financials gains, by reducing the cost of equipment maintenance and production losses; material gains by reducing premature deterioration of machines; and especially human gains by reducing the risks to which the operators are exposed.

Other parameters can be monitored in the same *HE*, like *pressure* and *FRs*. With the same manner, we can supervise entirely the parameters of the *HE* of the *secondary cooling circuit*. Besides *HE*s in the cooling circuits, there are other components to monitor especially *pumps.* Also, it is important to mention that these methods used to supervise the parameters of the first *HE*, can be also applied with the same manner on the second *HE* of cooling circuits of *LENA* reactor which is of the same type as the present *HE* with slight differences in characteristic coefficients. Furthermore, we can apply this supervising procedure to other important parameters in different reactor systems.

This work is performed offline, however, its implementation for online monitoring can be carried out efficiently using dedicated equipment installed at the reactor. Hence, the expected work of the present project will be the implementation of the developed algorithm, to supervise the *HE*s parameters, in standalone board using one of the *FPGA* chips. Other future activity is to generalize this work on some other types of *HEs*, by considering them as *NL* systems. This requires the use of the appropriate estimators as the *extended* and *unscented KFs.* Also, in future, for practical applications, the human-machine interface of this monitoring system will be improved by using *ES* technique. It can be noted that the *FMA* scheme and experiments presented in this thesis only addresses one failure once time. However, this scheme could be extended to address multiple failures (simultaneously or in series). Moreover, until now, we have essentially used *ARBMs* and *DDM* for the parameter estimations of the *HE* and the core of the *NRR*. Nevertheless, the use of simulation codes such as *RELAP* and *APROS* is important to extend this application to other reactor systems and process.

Annex : Notation

A - Nomenclature

Note: The word "Technique" is used instead "Methods" to do not make confusion with "Model" when abbreviation is used

Subscripts - h: hot, c: cold, i: inlet o: outlet and n = h or c

Notation	*Designation*
A_n	*Heat transfer (exchange) surface area of the fluid n, [m2]*
c_{pn}	*Specific heat of the fluid n, [J/(Kg°C)]*
C_n	*Heat (thermal) capacity or specific heat capacity of the fluid n, [W/°C]*
ε_n	*Effectiveness of the fluid n of the heat exchanger, [ ]*
Fc	*Correction factor, [ ]*
k_{eff}	*Effective Multiplication Factor*
Tf	*fuel temperature*
k	*Discrete Time*
$\dot{m}_n$	*Mass flow rate of the fluid n, [Kg/s]*
N	*Sample number of the data set*
Pn	*Nuclear Power*
$\dot{Q}_n$	*Heat transfer rate or heat power of the fluid n, [W]*
R	*Heat transfer rate ratio, [ ]*
ρ	*Reactivity*
ρ_n	*Density of the fluid n, [Kg/m3]*
T_{ni}, T_{no}	*Inlet and outlet temperatures of the fluid n, [°C]*
U_n	*Overall heat transfer coefficient of the fluid n, [W/(m2°C)]*
v_n	*Volume velocity, [m3/s]*
V_n	*Volume of the fluid n, [m3]*

B - Acronyms

These acronyms are used in *this thesis* for the interest of space

A

Abbreviation	*Designation*
AANN	*Auto-Associative Neural Network*
ABT	*Analytical-Based Technique*
AC	*Alternative Current*
ADS	*Aided Decision System*
AE	*Acoustic Emission*
AFDA	*Actuator Failure Detection and Accommodation*
AFDIA	*Actuator Failure Detection, Identification and Accommodation*
AFTC	*Active Fault-Tolerant Control*

AHU	*Air-Handling Unit*
AI	*Artificial Intelligence*
Pa	*All Power Regimes*
AMBT	*Analytical Model-based Technique*
AR	*Analytical Redundancy*
ARMA	*AutoRegressive Moving Average*
ARX	*AutoRegressive with eXogenous input*

B

BG	*Bond Graph*
BN	*Bayesian Network*
BWR	*Boiling Water Reactors*

C

CANDU	*Canada Deuterium Uranium*
CBM	*Condition-Based Maintenance*
CC	*Correlation Coefficient*
CE	*Cause-Effect*
CG	*Causal Graph*
CI	*Computational Intelligence*
CM	*Condition Monitoring*
CMd	*Combined Method*
CtM	*Continuous Monitoring*
CWT	*Continuous Wavelet Transform*

D

DC	*Direct Current*
DDT	*Data-Driven Technique*
DDMBT	*Data-Driven Model-Based Technique*
DFT	*Discrete Fourier Transform*
DM	*Decision-Making*
DOS	*Dedicated Observer Scheme*
DT	*Decision Tree*
DeNN	*Decentralized Neural Network*
DNN	*Dynamic Neural Network*
DR	*Data Reconciliation*
DSet	*Dominant Set*
DWT	*Discrete Wavelet Transform*

E

e-NTU	*Effectiveness - Number of Transfer Units*
EKF	*Extended Kalman Filter*
EMRAN	*Extended Minimal Resource Allocating Network*
ES	*Expert System*

F

FAc	*Fault Accommodation*
FAn	*Fault Analysis*
FAl	*False Alarm*
FDA	*Fault Detection and Accommodation*
FDD	*Fault Detection and Diagnosis*
FDe	*Fault Detection*
FDi	*Fault Diagnosis*
FDI	*Fault Detection and Identification / Isolation*
FDIA	*Fault Detection, Identification and accommodation*
FDIso	*Fault Detection and Isolation*
FDId	*Fault Detection and Identification*
FDIdIso	*Fault Detection, Identification and Isolation*
FEst	*Fault Estimation*
FFNN	*Feed Forward Neural Network*
FFT	*Fast Fourier Transform*
FiDiAn	*Fisher Discriminant Analysis*
FId	*Fault Identification*
FIso	*Fault Isolation*
FM	*Fault Monitoring*
FMA	*Fault Monitoring and Accommodation*
FMEA	*Failure Modes and Effects Analysis*
FL	*Fuzzy Logic*
FLo	*Fault Location (Localization)*
FNN	*Fuzzy Neural Network*
FPGA	*Field Programmable Gate Array*
FR	*Flow Rate*
FS	*Fault Supervision*
FT	*Fourier Transform*
FTA	*Fault Tree Analysis*
FTC	*Fault-Tolerant Control*
FTo	*Fault-Tolerance*
FTr	*Fault Tree*

G

GA	*Genetic Algorithm*
GMM	*Gaussian Mixture Model*
GOS	*Generalized Observer Scheme*
GP	*Graph of a Process*

H

HB	*Heat (Thermal) Balance*
HE	*Heat Exchanger*
HHT	*Hilbert-Huang transform*
HMM	*Hidden Markov Model*
HR	*Hardware Redundancy*

HTR	*Heat Transfer Rate*

I

IR	*Infrared*
I&C	*Instrumentation and Control*
ICA	*Independent Component Analysis*
IRT	*Infrared Thermography*

K

KBT	*Knowledge-Based Technique*
KDE	*Kernel Density Estimation*
KF	*Kalman Filter*
KICA	*Kernel Independent Component Analysis*
K-NN	*K-Nearest Neighbor*

L

LC	*Limit Checking*
LENA	*Laboratorio Energia Nucleare Applicata*
LMTD	*Log-Mean Temperature Difference*
LPMS	*Loose Part Monitoring Systems*
LR	*Logistic Regression*
LS	*Linear System*
LSE	*Linear State Equation*
LTIS	*Linear Time-Invariant System*

M

MAE	*Maximum Absolute Error*
MAE (%)	*Percent Maximum Absolute Error*
MeAE	*Mean Absolute Error*
MBT	*Model-Based Technique*
MCSA	*Motor-Current Signature Analysis*
MFR	*Mass Flow Rate*
ML	*Machine Learning*
MLP	*Multi-Layer Perceptron*
MLR	*Multivariate Linear Regression*
MM	*Mathematical Model*
MMBT	*Mathematical Model Technique*
MuM	*Multiple Model*
MSE	*Mean Square Error*
MSET	*Multivariate State Estimation Technique*

N

NARX	*NL Auto-Regressive with eXogenous inputs*
NF	*Neuro-Fuzzy*

NL	*Non-Linear*
NN	*Neural Network*
NOC	*Normal Operating Condition*
NP	*Nuclear Plant*
NPP	*Nuclear Power Plant*
NPR	*Nuclear Power Reactor*
NR	*Nuclear Reactor*
NRR	*Nuclear Research Reactor*

O

OLA	*Online Approximation*
OLM	*On-line Monitoring*
Or	*Operating Regime*

P

PCA	*Principal Component Analysis*
PCR	*Principal Component Regression*
Pd	*Power Down*
PI	*Proportional And Integral*
PoI	*Power Interrupt*
PLS	*Partial Least-Squares*
PR	*Pattern Recognition*
PNN	*Probabilistic Neural Networks*
PSA	*Power Signature Analysis*
PSD	*Power Spectral Density*
Pu	*Power Up*
PWR	*Pressurized Water Reactor*

R

RMAE	*Relative Mean Absolute Error*
RNN	*Recurrent Neural Network*
RMSE	*Root Mean Square Error*
RCS	*Reactor Coolant System*
RBF	*Radial Basis Function*

S

SA	*Spectral Analysis*
SCADA	*Supervisory, Control, and Data Acquisition*
S/D	*Sensor and Detector*
SDG	*Signed Direct Digraph*
SFA	*Sensor Failure Accommodation*
SFDA	*Sensor Failure Detection and Accommodation*
SFDIA	*Sensor Failure Detection, Identification and Accommodation*
SiBT	*Signal-Based Technique*
SLP	*Single-Layer Perceptron*

SMAPE	*Symmetric Mean Absolute Percentage Error*
SNN	*Static neural network*
SP	*Signal Processing*
SPND	*Self-Powered Neutron Detector*
S/P	*System/Process*
SeV	*Sensor Validation*
SOM	*Self-Organizing Map*
SSME	*Space Shuttle Main Engine*
SR	*System Reconfiguration*
STFT	*Short-Time Fourier Transform*
SVDD	*Support Vector Data Description*
SVM	*Support Vector Machine*

T

TDNN	*Time Delay Neural Network*
TDRNN	*Time Delay Recurrent Neural Network*
TFA	*Time-Frequency Analysis*
TI	*Transient Identification*
Triga	*Training Research* and *Isotope Production General Atomic*
TSOM	*Temporal Kohonen Map*

U

UAV	*Unmanned Air Vehicle*
UIO	*Unknown Input Observer*
UKF	*Unscented Kalman Filter*

W

WPT	*Wavelet Packet Transform*
WSN	*Wireless Sensor Network*
WT	*Wavelet Transform*
WVD	*Wigner-Ville Distribution*

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