UNIVERSITE SAAD DAHLAB DE BLIDA 1

Faculté des Sciences de l'Ingénieur

Département d'Electronique

MEMOIRE DE MAGISTER

en Eléctronique

Spécialité : Signaux et Systèmes

PERFORMANCE IMPROVEMENT AND SMART GRID OPTIMIZATION

Par

Dassa Khaled

devant le jury composé de :

A. Guessoum	Professeur, U.de Blida 1	Président
H. Meliani	Professeur, U. de Blida 1	Examinateur
A. Bentarzi	Professeur, U. de Boumerdes	Examinateur
H. Salhi	Professeur , U. de Blida 1	Copromoteur
A.Recioui	Maitre de conférences, U. de Boumerdes	Promoteur

Blida, Janvier 2016

DEDECATION

I dedicate this modest work to:

My beloved mother and my father who take care of me since I was child

My brothers and sisters.

All my friends each one with his name.

My teachers Amar and Mohamed.

My fiancée and partner of my life Asma Elbaraa.

ABSTRACT

Electrcity energy sources are unsustainable and that forces the world to search for other sustainable sources that can provide reliable and efficient power. With the recent issues which grids are facing, the idea of Smart Grid was born. This project is a step to enter smart grid field by touching some basic sides, it solves the optimal placement problem of phasor measurement unit by a suggested version of the teaching-learning based optimization. Also a comparison between TLBO and other optimization methods (Genetic Algorithm GA, Ant Colony AC…) is made .

In the second part, integration of renewable energies sources was done by the most well-known tool in this field which is HOMER firstly, the studied are is In Salah, secondly the integration was done by TLBO and then the two ways was compared to each other to see the advantages and disadvantages of each one. In addition to that, two control strategies had been built similar to those of HOMER. A comparison had been made from the sides of costs and globality.

Résumé

Les sources d'énergie d'électricité sont qualifier de non-permanentes ce qui a obligé le monde à chercher d'autres sources permanentes qui peuvent fournir une énergie fiable et efficace. Avec les problèmes récents que le réseau électrique affronte, l'idée de réseau électrique intelligent a été née.

Ce projet est une étape pour s'initier dans le domaine des réseaux intelligents toute en abordant certaines parties de base, son but est de résoudre le problème de placement optimal de PMU par une version proposé de TLBO. Une comparaison entre TLBO et d'autres méthodes d'optimisation a été illustré tel que l'algorithme génétique GA, Colonie de fourmilles AC, ...
Dans la deuxième partie, l'intégration des énergies renouvelables a été réalisé par l'outil le plus connu dans ce domaine à savoir Homer d'abord, (la région d'étude de Ain Salah), après on a fait l'intégration par TLBO, puis les deux outils ont été comparée pour voir les avantages et les inconvénients de chacun de ces outils. En plus, deux stratégies de contrôle ont été développées similaire à ceux d'HOMER. Une comparaison a été réalisée entre ces stratégies sur le plan du coût et de globalité.

الـــمـــلـــخـــــــص

إن مصادر الطاقة الكهربائية غير دائمة وهذا ما ترك العالم يتوجه إلى البحث عن مصادر طاقوية دائمة قادرة على توليد طاقة موثوق فيها وفعالة. وقد ولدت الصعوبات التي تواجها الشبكة الكهربائية فكرة الشبكة الكهربائية الذكية.

هذا العمل هو عبارة على مدخل إلى الشبكات الذكية وولوج إليها بلمس بعض الجوانب المهمة فيها. هذا التقرير يعرض كيفية تنصيب وحدة قياس المتجهات بطريقة مثالية وذلك باتباع خوارزمية الإستمثال بالتعليم والتعلم التي تعد نجمة ساطعة مع أخواتها في مجال الإستمثال كما أنه يقترح نسخة ثنائية لهذه الخوارزمية مع المقارنة بالخوارزميات المشهورة في هذا المجال كالخوارزمية الجينية وخوارزمية مجتمع النمل ...إلخ.

وفي الجزء الثاني يعرض هذا العمل كيفية دمج المصادر الطاقوية المتجددة في الأنظمة الطاقوية الصغيرة والمعزولة وذلك بدراسة المشروع في منطقة "عين صالح" باستخدام الأداة الشهيرة وهي HOMER أولا واستخدام خوارزمية الإستمثال بالتعليم والتعلم ثانيا. وفي الأخير مقارنة بين الطريقتين لمعرفة محاسن ومساوئ كل طريقة. وخلال المحور الأخير كذلك تم بناء استراتيجيتين للتحكم بالطاقة شبيهتين ب استراتيجيات HOMER وقد تمت المقارنة بين الطرفين من ناحية الكلفة والشمول.

ACKNOWLEDGEMENTS

Alhamdulillah, Praise and glorification be only to Allah SWT, the Almighty, the most beneficent and the most merciful, whose blessing and guidance have helped me to finish this work.

I would like to express our sincere gratitude and thanks to my supervisor Dr.Recioui Abdelmadjid for his encouragement and guidance during the period of this project.

My warm thanks to all IGEE (Institut de Genie Electrique et Electronique) teachers who all contributed in some way or another to this project. Special thanks to Mr. Hariche, Mr. Kribes.

In a time science is precious and rare, the University of Blida opened its gates to me and gives me a chance to complete my study, so my special thanks goes to its teachers and workers.

I would like to express my deepest gratitude to my advisor, Pr. Salhi Hassen, for his support and guidance throughout the report.

TABLE OF CONTENTS

List of Figures

LISTE OF TABLES

LIST OF ABBREVIATIONS

ADC	Analogue to Digital Conversion.
ASS	Application Software Servers.
ABC	Artificial Bee Colony.
BTLBO	Binary Teaching-Learning Based Optimization
CC	Cycle-Charging.
COE	Cost of Energy.
CT	Current Transformer.
DNO	Distribution Network Operator.
DR	Demand Response
DSI	Demand Side Integration.
DSM	Demand-Side Management.
EMS	Energy Management System.
FACTS	Flexible AC Transmission System.
GA	Genetic Algorithm.
GHI	Global Horizontal Irradiance.
GPS	Global Positioning System.
HAN	Home Area Network.
HVDC	High Voltage Direct Current.
IEEE	Institue of Electrical and Electronic Engineering.
ICT	Information and Communication Technology
IED	Intelligent Electronic Device.
LF	Load-Following.
LPS	Loss of Power Supply.
LPSP	Loss of Power Supply Probability.
NAN	Neighborhood Area Network.
NPC	Net Present Cost.
NREL	National Renewable Energy Laboratory in USA.
O&M	Maintenance and Operation Cost.
OPP	Optimal Placement Problem.
PSO	Particle Swarm Optimization.
PMU	Phasor Measument Unit.
PLC	Programmable Logic Controller.

RES	Renewable Energies Sources.
RTU	Remote Terminal Unit.
SCADA	Supervisory Control And Data Acquisition.
SCDR	Symmetrical Component Distance Relay.
SOC	State Of Charge.
SMT	Synchronized Measurement Technology.
TLBO	Teaching-Learning-Based Optimization.
THD	Total Harmonic Distortion.
TNPC	Total Net Present Cost.
UPFC	Unified Power Flow Controllers.
VT	Voltage Transformers.
WAMS	Wide Area Monitoring System.
WAMPAC	Wide Area Monitoring, Protection and Control.
WAN	Wide Area Network.

INTRODUCTION

In many areas of the country, the only way a utility knows there's an outage is when a customer calls to report it. Most blackouts are caused by the continuous increasing population which makes the grid unable to meet efficiently the demand for reliable power supply. That issue was studied through years and years to give in the end the born of a new grid or at least the idea of a grid that can predict, adapt, and reconfigure itself efficiently and reliably and that how the idea of "Smart Grid" comes to appearance.

The power in Today's grid flows in one direction from the distribution circuit to the customer however; Smart grid allows the power to travel in both directions moreover; the information and control signals are also flowing bidirectionally.

In order to cover the entire demands Smart grid uses the renewable energies as other sources to support traditional sources, which make the grid cleaner and less pollutant.

Smart grids present a strategies to organize the consuming of the electrical energy to reduce the peak load and therefore less power will be lost, those strategies are done through what's called the Demand Side Integration (DSI), Demand-Side Management (DSM), Demand Response (DR)…… those terms have close meaning but all of them are targeting at consuming power wisely.

Smart grid provides a full observability of the system; it includes a real time monitoring technologies like phasor measurement units (PMUs), smart meters, intelligent devices (IEDs), furthermore smart grid allows the Distribution Network Operators to control smart appliances in each house of the grid.

An old adage says "You can't control what you don't measure", so the observability of a system is so important to control it, not just a full observability is needed but a high synchronized information of the system is mandatory for the control and the management of power and even the system protection.

Wide-area monitoring, protection, and control require communicating the specific-node information to a remote station but all information should be time synchronized so that to neutralize the time difference between information. The conventional system is not able to satisfy the time-synchronized requirement of power system. Phasor Measurement Unit (PMU) is enabler of time-synchronized measurement [1] [2].

Recently, PMUs equipped with global positioning system GPS is applied in power systems monitoring and state estimation. PMUs can directly measure the voltage amplitudes and phase angles of key buses in power systems with high accuracy. Since GPS provides negligible synchronization error, the interests are concentrated on where and how many PMUs should be implemented in a power system with the smallest cost and with the largest degree of observability and that‘s the optimal placement problem (OPP) of PMU. OPP research was treated by many optimization methods, in this report in chapter 2 the OPP problem was solved by the teaching learning based optimization.

In recent years, a considerable growth in using renewable energy resources has been observed, especially solar and wind energy which are infinite, site-dependent, clean and high potential sources for alternative energy production. Hybrid energy systems are the best suited to reduce dependence on fossil fuel using available wind speed and solar radiations. The integration of renewable energy sources is not a straightforward operation but it needs a techno-economical analysis and requires full data of the renewable resources.

Sizing hybrid systems have been in the last two decades a large research field and many methods have been suggested to solve that problem and still the research is carrying on, and that returns to the modeling accuracy of components of the hybrid system and the followed power management strategies. The control strategy is the heart beating of any algorithm subjected to optimize a hybrid system, in 1996 Barley and Winn[3] improved the control strategies model of[4], introducing new parameters that have become of great importance in the control strategies of the software tools HYBRID2, HOMER and HOGA[5].

HOMER (Hybrid Optimization Model for Electric Renewables)[6], developed by NREL (National Renewable Energy Laboratory in USA), is the most-used optimization software for hybrid systems. It uses a predictive control strategy where the charging of the batteries depends on the prediction of the demand and the energy expected to be generated by means of renewable sources, with this strategy, the energy loss from the renewable energies tends to decrease. In chapter 3 HOMER was used to optimize a test hybrid system in In Salah (Algeria) to see the successfulness and the powerfulness of the area. Another method was used to optimize the system which has a quite similar control strategy without the predicting side; this method is one of the most recent stars in the field of metaheuristic methods, it is called “Teaching-learning-based algorithm” (TLBO). The suggested TLBO uses the loss of power supply probability (LPSP) as the reliability restriction minimizing the total Net Present Cost (TNPC), the results obtained by each tool will be evaluated by that economic criterion.

The main parts of this report are:

- Generalities about smart grid.
- PMU placement using the teaching learning based optimization.
- Integration of renewable energy sources using HOMER.
- Integration of renewable energy sources using TLBO.

And finally, a conclusion is deduced summarizing all the results and recommendations.

Chapter 1: Generalities about smart grid.

1.1 Introduction

Electric power infrastructure that has served us so well for so long is facing many issues and challenges with continuous growing of its size. Consumers usually don't know what risks are troubling their comfort. It seems that the humanity near agenda is formidable, but a brilliant idea was born to solve those issues and in some way everybody is agree with it, it is the Smart grid.

Smart grid comes to face the problem of the load growing, the unsustainability of energy sources and the non-corporation of consumers with a high technologies and well-established mechanisms to ensure the reliability and efficiency of power. Furthermore, it has the ability of healing itself or at least stopping or enclosing problems when they occur. Smart grid is a large research area since all the fields are merged into it, it includes communication, control, power system protection, digital system, optimization methods…etc. Smart Grid is characterized by a two-way flow of electricity and information (Figure 1-1) and its ability of monitoring everything from power plants to customer preferences to individual appliances.

1.1.1 Definition:[7]

The European Technology Platform defines the Smart Grid as:

"*A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies.*"

The new grid will be capable of: [8]

1. managing the consumer load pattern through smart meters and smart appliances, also providing enough information about the prices and energy use to consumers and even the consumer can sell power in somehow. This is technically the Demand Side Management (DSM)

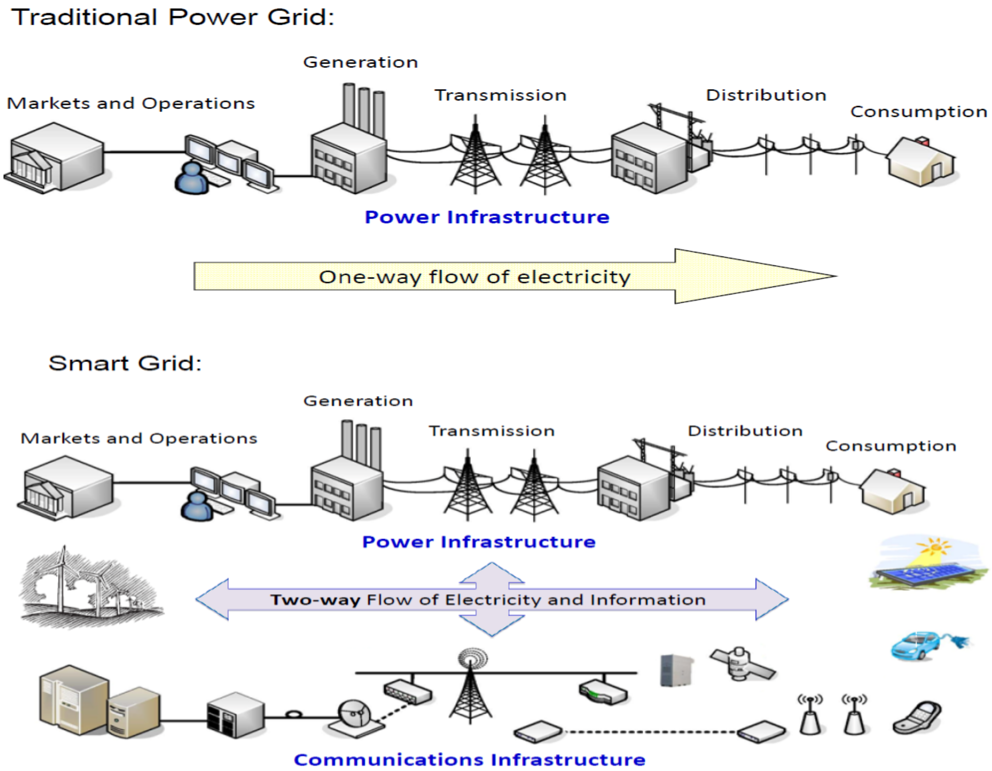


Figure 1-1 traditional grid and smart grid [**9**].

2. integrating the renewable energies to produce electricity especially in rural areas, as well as allowing residential micro-generation in which the consumer can sell even the power.
3. Optimizing the use of power by finding the optimal management way to serve efficiently and at the exact time the load
4. Assuring and improving reliability and the security of supply by being resilient to disturbances, attacks and natural disasters, anticipating and responding to system disturbances (predictive maintenance and self-healing), and strengthening the security of supply through enhanced transfer capabilities.
5. Maintaining the power quality of the electricity supply to cater for sensitive equipment that increases with the digital economy.
6. Opening access to the markets through increased transmission paths, aggregated supply and demand response initiatives and ancillary service provisions.

1.2 Comparison of Today ' s Grid vs. Smart Grid [10]

Preferred Characteristics	Today ' s Grid	Smart Grid
Active Consumer Participation	Consumers are uninformed and do not participate	Informed, involved consumers demand response and distributed energy resources
Accommodation of all generation and storage options	Dominated by central generation — many obstacles exist for distributed energy resources interconnection	Many distributed energy resources with plug - and –play convenience focus on renewables
New products, services, and markets	Limited, poorly integrated wholesale markets; limited opportunities for consumers	Mature, well - integrated wholesale markets; growth of new electricity markets for consumers
Provision of power quality for the digital economy	Focus on outages — slow response to power quality issues	Power quality a priority with a variety of quality/price options rapid resolution of issues
Optimization of assets and operates efficiently	Little integration of operational data with asset management business process silos	Greatly expanded data acquisition of grid parameters; focus on prevention, minimizing impact to consumers
Anticipating responses to system disturbances (self- healing)	Responds to prevent further damage; focus on protecting assets	Automatically detects and responds to problems; focus on prevention,

	following a fault	minimizing impact to consumers
Resiliency against cyber attack and natural disasters	Vulnerable to malicious acts of terror and natural disasters; slow response	Resilient to cyber-attack and natural disasters; rapid restoration capabilities

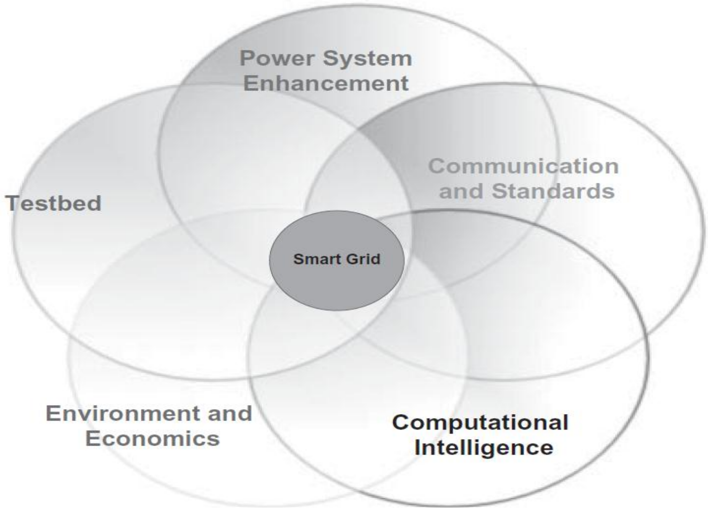


Figure 1-2 Five key aspects of smart grid development [10].

As Figure 1-2 shows, there are five key aspects of smart grid development and deployment.

a. <u>Computational intelligence:</u>

Computational intelligence is the term used to describe the advanced analytical tools needed to optimize the bulk power network. The toolbox will include heuristic, evolution programming, decision support tools, and adaptive optimization techniques.

b. <u>Power system enhancement:</u>

Policy - makers assume that greatly expanded use of renewable energy resources will help to offset the impacts of carbon emissions from thermal and fossil energy, meet demand uncertainty, and to some extent, increase reliability of delivery.

c. <u>Communication and standards:</u>

Since planning horizons can be short as an hour ahead, the smart grid's advanced automations will generate vast amounts of operational data in a rapid decision making environment. New algorithms will help it become adaptive and capable of predicting with foresight. In turn, new rules will be needed for managing, operating, and marketing networks.

d. <u>Environment and economics:</u>

Based on these desired features, an assessment of the differences in the characteristics of the present power grid and the proposed smart grid is needed to highlight characteristics of the grid and the challenges. When fully developed the smart grid system will allow customer involvement, enhance generation and transmission with tools to allow minimization of system vulnerability, resiliency, reliability, adequacy and power quality.

e. <u>Testbed:</u>

The training tools and capacity development to manage and operate the grids and hence crate new job opportunities is part of the desired goals of the smart grid evolution which will be tested using test - bed. To achieve the rapid deployment of the grids test bed and research centers need to work across disciplines to build the first generation of smart grid.

1.3 <u>Overview of the technologies required for the Smart Grid</u> [11]

Smart Grid includes the following technologies:

a. <u>Information and communications technologies:</u> These include:

(1) Two-way communication technologies to provide connectivity between different components in the power system and loads.

(2) Open architectures for plug-and-play of home appliances; electric vehicles and micro generation.

(3) Communications, and the necessary software and hardware to provide customers with greater information, enable customers to trade in energy markets and enable customers to provide demand-side response.

(4) Software to ensure and maintain the security of information and standards to provide scalability and interoperability of information and communication systems.

b. Sensing, measurement, control and automation technologies: These include:

(1) Intelligent Electronic Devices (IED) to provide advanced protective relaying, measurements, fault records and event records for the power system.

(2) Phasor Measurement Units (PMU) and Wide Area Monitoring, Protection and Control (WAMPAC) to ensure the security of the power system, PMU is discussed in chapter 2 with more details.

(3) Integrated sensors, measurements, control and automation systems and information and communication technologies to provide rapid diagnosis and timely response to any event in different parts of the power system. These will support enhanced asset management and efficient operation of power system components, to help relieve congestion in transmission and distribution circuits and to prevent or minimize potential outages and enable working autonomously when conditions require quick resolution.

(4) Smart appliances, communication, controls and -monitors to maximize safety, comfort, convenience, and energy savings of homes.

(5) Smart meters, communication, displays and associated software to allow customers to have greater choice and control over electricity and gas use. They will provide consumers with accurate bills, along with faster and easier supplier switching, to give consumers accurate real-time information on their electricity and gas use and other related information and to enable demand management and demand side participation, Smart meter will be discussed later.

c. Power electronics and energy storage: it includes:

(1) High Voltage DC (HVDC) transmission and back-to-back schemes and Flexible AC Transmission Systems (FACTS) to enable long distance transport and integration of renewable energy sources.

(2) Different power electronic interfaces and power electronic supporting devices to provide efficient connection of renewable energy sources and energy storage devices.

(3) Series capacitors, Unified Power Flow Controllers (UPFC) and other FACTS devices to provide greater control over power flows in the AC grid.

(4) HVDC, FACTS and active filters together with integrated communication and control to ensure greater system flexibility, supply reliability and power quality.

(5) Power electronic interfaces and integrated communication and control to support system operations by controlling renewable energy sources, energy storage and consumer loads.

(6) Energy storage to facilitate greater flexibility and reliability of the power system.

The integration of renewable energy sources is discussed in chapter 3 of this report.

1.4 Communication Technologies for the Smart Grid

In principle, SCADA system and the System Control Centre both connected by a dedicated communication channel and Wide Area Network (WAN) are the typical communication infrastructure of a power system.

The SCADA systems connect all the major power system operational facilities, that is, the central generating stations, the transmission grid substations and the primary distribution substations to the System Control Centre. The WAN is used for corporate business and market operations. These form the core communication networks of the traditional power system.

The invention of smart grid comes to connect all the distribution network and HAN of customers in one bidirectional and well sophisticated grid through NAN(Figure 1-3). The interface of the Home and Neighborhood Area Networks will be through a smart meter or smart interfacing device.

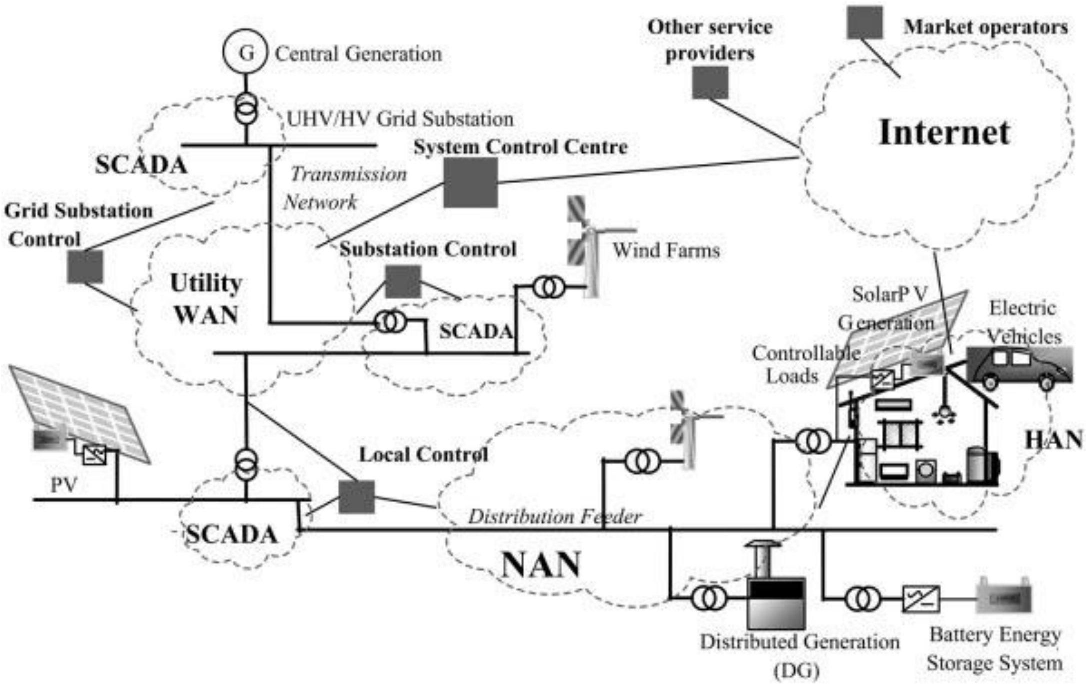


Figure 1-3 Possible communication infrastructure for the Smart Grid [8].

Each basic component in Figure 1-3 will be explained alone.

1.4.1 SCADA:[12]

The definition of SCADA is ‘Supervisory Control and Data Acquisition’. The major function of SCADA is for acquiring data from remote devices such as valves, pumps, transmitters etc. and providing overall control remotely from a SCADA Host software platform. This provides process control locally so that these devices turn on and off at the right time, supporting the control strategy and a remote method of capturing data and events (alarms) for monitoring these processes. SCADA Host platforms also provide functions for graphical displays, alarming, trending and historical storage of data.

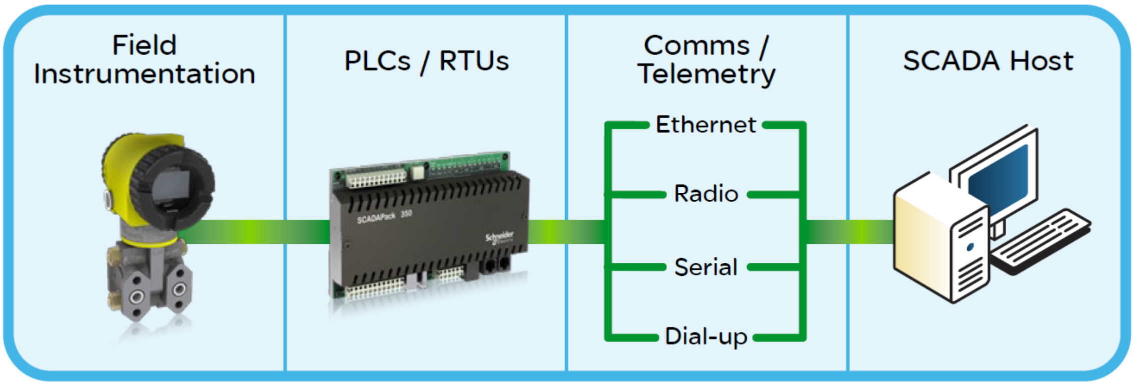


Figure 1-4 SCADA System Overview [12].

There are four distinct levels within SCADA (Figure 1-4), these being: [12]

i. Field instrumentation,

ii. PLCs and / or RTUs,

iii. Communications networks and

iv. SCADA host software.

a. Field instrumentation: This includes sensors and all equipment used to control and monitor the flow of electrical energy, instrumentation is the key component of a safe and optimized control system.

b. Remote Terminal Unit (RTU): The RTU, also called a remote telemetry unit, is used for data acquisition and control unit supporting SCADA remote stations.. Sometimes PLCs are implemented as field devices to serve as RTUs; in this case, the PLC is often referred to as an RTU.

c. Programmable Logic Controller (PLC): The PLC is a small industrial computer originally designed to perform the logic functions executed by electrical hardware (relays, drum switches, and mechanical timer/counters).

d. Communications Networks: The communication network links between all the parts which means that it is the glue in the functionality of the SCADA system , the transfer of the data provided by the field instruments is through the communication networks. How well a SCADA system can manage communication to remote assets is fundamental to how successful the SCADA system is.

1.4.2 Different communication networks:

- HAN (Home Area Network): The network that allows devices located within a home to communicate with each other. In the smart grid context, these devices could include smart meters, smart appliances, and home energy management devices.
- NAN (Neighborhood Area Network) and LAN (Local Area Network). The network that allows devices in a small area, such as a neighborhood, to communicate with each other. For example, all the smart meters in a neighborhood may communicate with each other and with a router to form an interconnected mesh of smart devices.

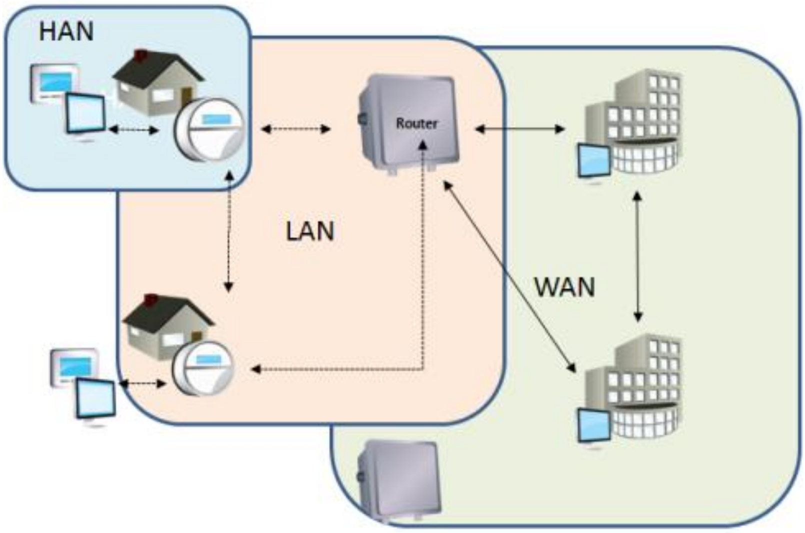


Figure 1-5 ANs Networks[13].

- WAN (Wide Area Network): A network that can allow devices within a large geographic area to communicate with each other. For example several meter data collectors, mobile meter readers, and substation automation devices might send information to the utility offices over a WAN.

1.5 Information Security for the Smart Grid

Smart grid advantage is the integration of everything in a single network but that can be also a disadvantage since the enlargement of the grid will create other challenges to secure information and data or in technical word the grid will be vulnerable to theft of data or malicious cyber-attacks.

Any form of interruption resulting from security issues is likely to have serious effects on the reliable and safe operation of the Smart Grid.

Security measures should ensure the following:

1. *Privacy* that only the sender and intended receiver(s) can understand the content of a message.
2. *Integrity* that the message arrives in time at the receiver in exactly the same way it was sent.
3. *Message authentication* that the receiver can be sure of the sender's identity and that the message does not come from an imposter.
4. *Non-repudiation* that a receiver is able to prove that a message came from a specific sender and the sender is unable to deny sending the message. It is performed through many types of digital signature which proves that a sender sends to another side (receiver) a message that cannot be modified. Approaches for digitally signing messages include the secret Key signature, the public Key signature and the message digest.

Information and Communication Technology (ICT) is developed in way to secure information and since the internet becomes the main communication mode, new mechanisms which are well-established are used to encrypt data and information and to authenticate the identities of users in communication sessions.

1.6 Sensing, Measurement, Control and Automation Technologies

To use electrical energy in an economic way and face the load growth problem, demand-side programs have been introduced widely.

There are various terms in use in the demand side (*Demand-Side Management (DSM)*, *Demand Response (DR), Demand-Side Participation, Demand-Side Integration (DSI)…)* whose meanings are closely related to each other but with slightly different focuses, but all of them are strategies that integrate customers to cooperate in the management of power.

The success of the implementation of the DSM depends strongly on the knowledge of system loads. However, the electro-mechanical meters that are presently installed in domestic premises have little or no communication ability and do not transmit information of the load in real time. Smart metering refers to systems that measure, collect, analysis, and manage energy use using advanced ICT.

Smart meter has a great role in the good functioning of the DSM by since it allows the transfer of data in two ways and it provides a real-time or at least a near-real-time.

1.6.1 Smart metering: [9]

Electricity meters are the eyes and ears of the grid in order to control the system, they are used to measure the power in all the levels of serving the load starting from the energy suppliers, passing the through the distribution networks and ending at the customer loads. Accumulation meters which record the energy consumption over time are used for that purpose. Building and forming tariffs and bills are based on how much the energy suppliers have knowledge about the flowing of power as well as the good design of the whole payment bill helps the consumers understand and manage their electricity demands. Smart meters are even more sophisticated as they have two-way communications and provide a real-time display of energy use and pricing information, dynamic tariffs and facilitate the automatic control of electrical appliances.

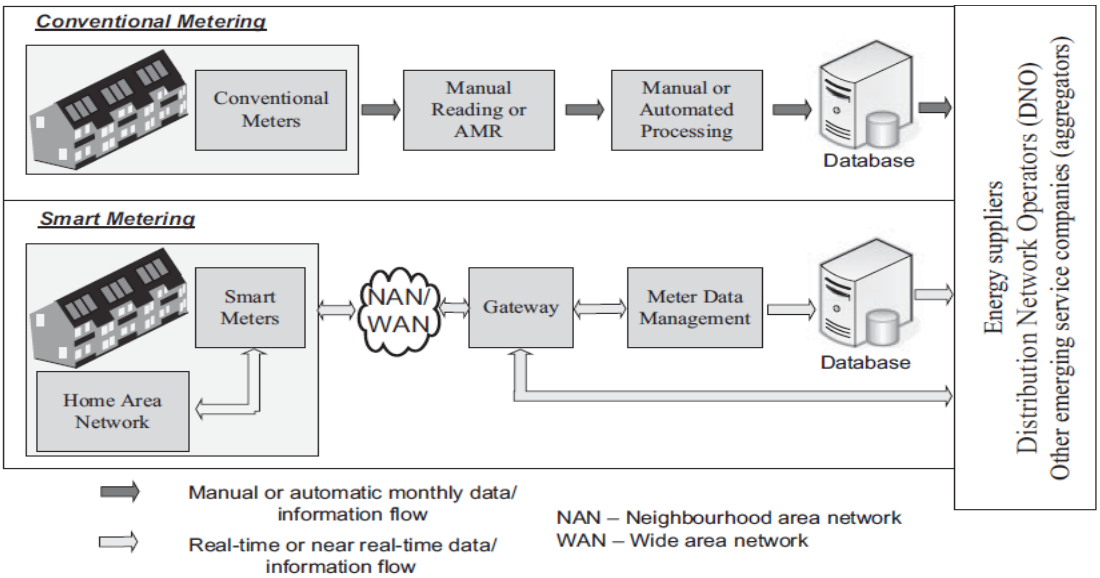


Figure 1-6 Conventional and smart metering compared[8]

As it is illustrated in Figure 1-6, smart meters have two-way communications to a Gateway and/or a Home Area Network (HAN) controller. The Gateway provides to smart meters access to send and receive data to and from Distribution Network Operators.

The smart meter architecture has been split into five sections (Figure 1-7): signal acquisition, signal conditioning, Analogue to Digital Conversion (ADC), computation and communication.

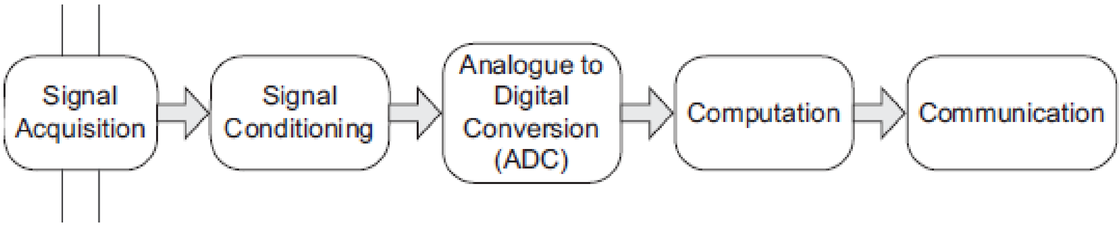


Figure 1-7 Functional block diagram of a smart meter [8].

a. <u>Signal acquisition:</u>

A core function of the smart meter is to acquire system parameters accurately and continuously for subsequent computation and communication. The fundamental electrical parameters required are the magnitude and frequency of the voltage and the magnitude and phase displacement (relative to the voltage) of current. Other parameters such as the power factor, the active/reactive power, and Total Harmonic Distortion (THD) are computed using these fundamental quantities.

b. <u>Signal conditioning:</u>

It is usually maps linearly "High Voltages" into "Low Voltage" in order to be acceptable at the input of ADC. The signal conditioning stage may include addition/subtraction, attenuation/amplification and filtering.

c. <u>Analogue to digital conversion:</u>

The ADC converts analogue signals coming from the sensors into a digital form with a certain resolution as it is needed to be. There are many established methods for conversion of an analogue input signal to a digital output (successive approximation method, sigma-delta method…).

d. <u>Computation:</u>

The computation requirements are split into arithmetic operations on input signals, time stamping of data, preparation of data for communication or output peripherals, handling of routines associated with irregular input (such as payment, tamper detection), storage of data, system updates and co-coordinating different functions.

1.7 Demand-side management [14] [15]

DSM is one of the most features of Smart grid, it is a set of measures to use loads and local generation to support network operation/management and improve the quality of power supply.

Demand-side resources such as flexible loads, distributed generation and storage can provide various services to the power system by modifying the load consumption patterns. Such services can include load shifting, valley filling, peak clipping, dynamic energy management, energy efficiency improvement and strategic load growth.

a. Load shifting:

The consumer just change the time of use of his load for example he was using the washing machine (Figure 1-8) between 18:00 and 20:00, now he should use it between 0:00 and 2:00.

b. Valley filling

The consumer to introduce an extra load in the peak off time but not any load , loads that store energy (Figure 1-9) like batteries and electric vehicules in order to be used later.

c. Peak clipping:

Consumers scarify by their comfort to help the grid relaxing specially when the thermal limits of transformers is reached, and this can be done through reducing thermostat of the cooling machines (Figure 1-10)

d. Energy efficiency improvement:

It is replacing the old appliances specially which consumes much power by energy-efficient appliances which economize the use of energy and do the same function

Figure 1-11 shows the reduction in energy demand when ten 60 W filament lamps (operating from 18:00 to 22:00) are replaced by 20 W Compact fluorescent lamps.

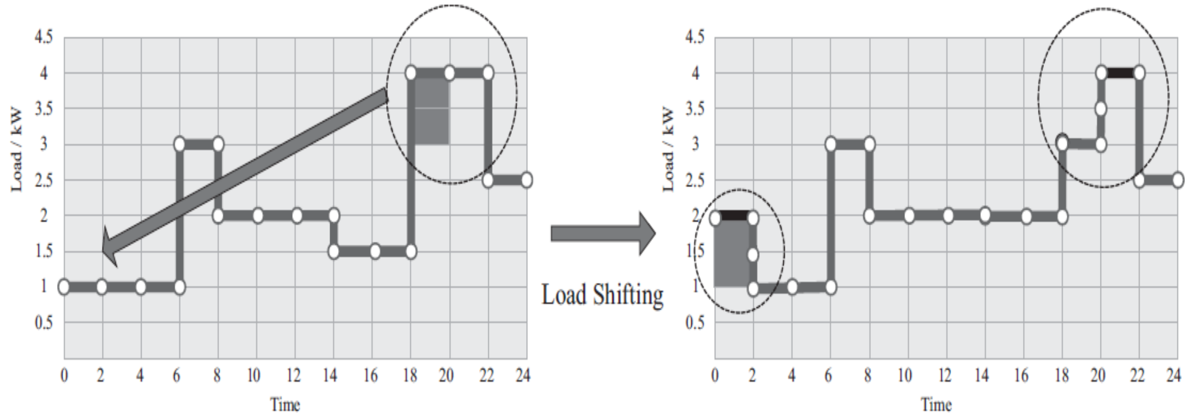


Figure 1-8 Load shifting [8].

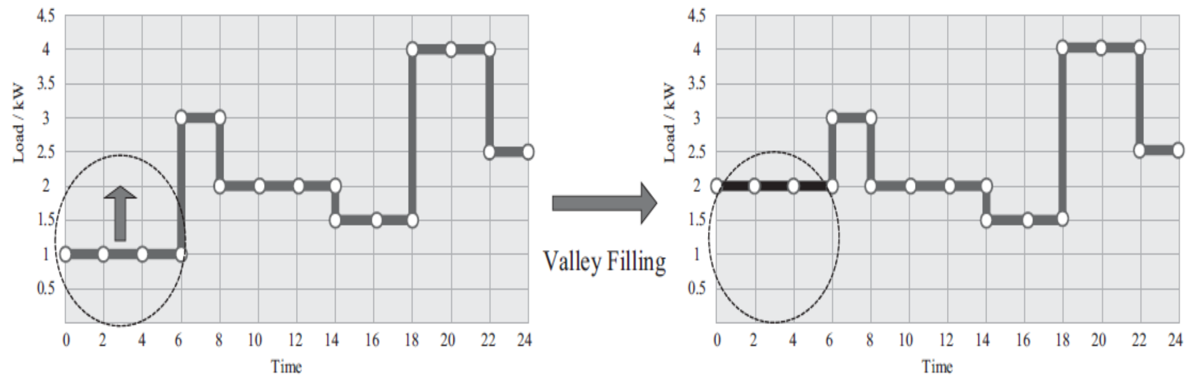


Figure 1-9 Valley Filling [8].

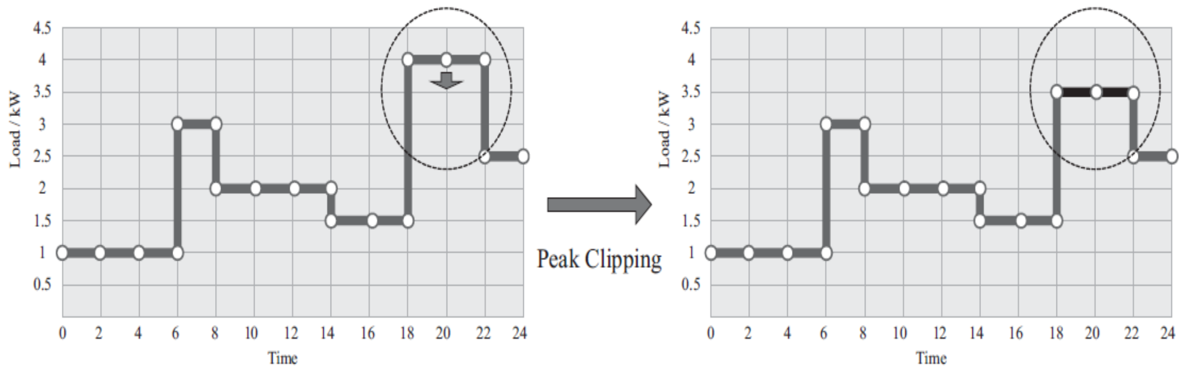


Figure 1-10 Peak Clipping [8].

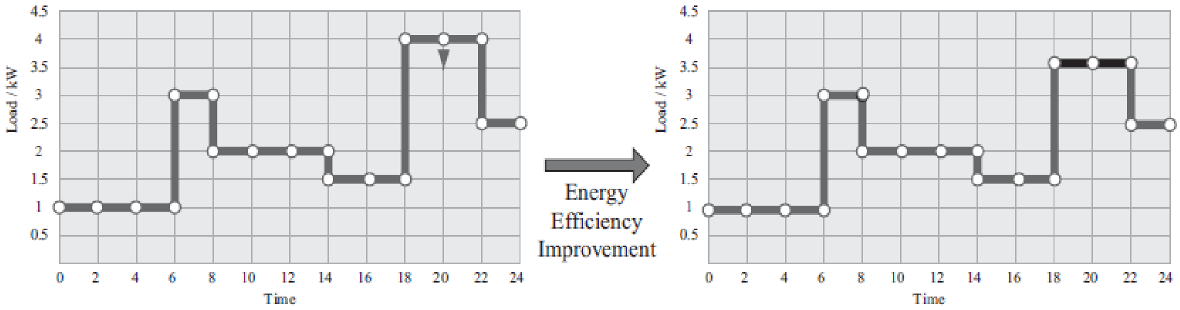


Figure 1-11 Energy Efficiency Improvement [8].

1.8 Distribution Automation Equipment

Modern electric power systems are supplied by large central generators that feed power into a high voltage interconnected transmission network. The power, often transmitted over long distances, is then passed down through a series of distribution transformers to final circuits for delivery to customers (Figure 1-12).

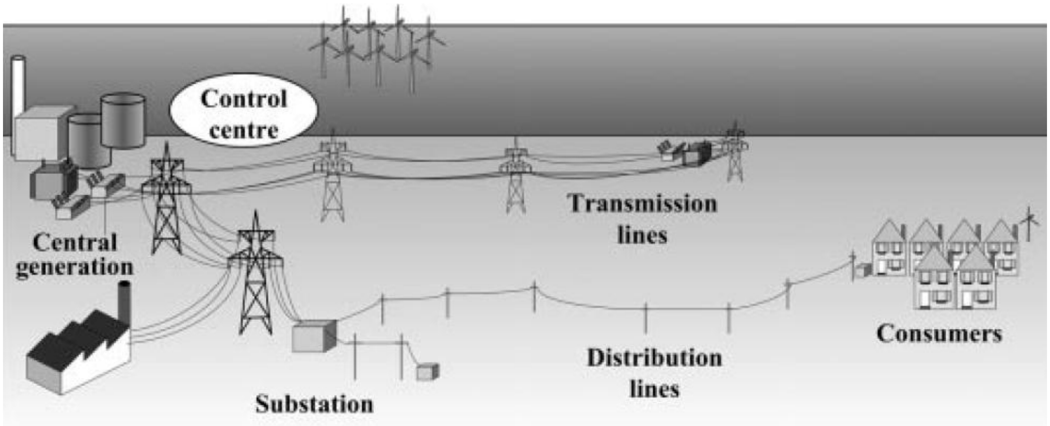


Figure 1-12 Typical power system elements [8].

Operation of the generation and transmission systems is monitored and controlled by Supervisory Control and Data Acquisition (SCADA) systems. These link the various elements through communication networks (for example, microwave and fiber optic circuits) and connect the transmission substations and generators to a manned control center that maintains system security and facilitates integrated operation.

Traditionally, the distribution network has been passive with limited communication between elements. Some local automation functions are used such as on-load tap changers and shunt capacitors for voltage control and circuit breakers or auto-reclosers for fault management. These controllers operate with only local measurements and wide-area coordinated control is not used. One of the most features of modern substation is the intelligent electronic device.

Intelligent electronic devices

The name Intelligent Electronic Device (IED) describes a range of devices that perform one or more of functions of protection, measurement, fault recording and control. An IED consists of a signal processing unit, a microprocessor with input and output devices, and a communication interface.

1.9 Transmission System [16]

With the increasing of renewable energy sources penetration and sizes of grids, transmission systems are facing more challenges. The randomness change in the load and the fluctuation in the power output of renewable energy sources cause difficulties for the system operators, who are responsible for maintaining the stability of the system i.e. maintaining the frequency at 60 Hz and that issue is known by *"balancing between generation and demand"*.

As Figure 1-13 indicates, if generators supply more than enough energy the frequency goes higher than 60 Hz and this will damage equipments of customers of the grid or at least they will not operate properly and then the grid must sell the extra energy to neighborhood grids or dump it in dump loads. In the other hand if the demand is more than the supplied power, a lack of energy will occurs and frequency will be under 60 Hz and then the grid needs to buy power from neighborhood grids to cover its lack or it should use the operating reserves if they are available. In addition to that the change in frequency will change the impedance of capacitors and inductors which will complicate the situation.

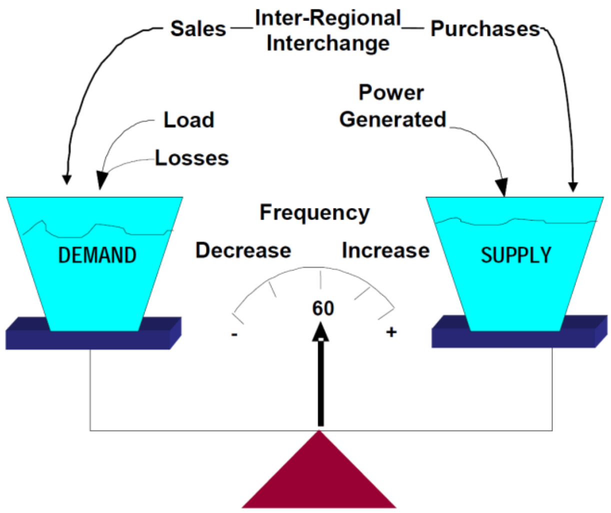


Figure 1-13 Generation / Demand Balance [16].

The system operators monitor, control and optimize the transmission system through a set of applications called "Energy Management System (EMS) ". With the growing availability of measurements from Phasor Measurement Units (PMUs), it is expected that, in future, PMU measurements will be integrated with EMS. However, at present, PMUs are mainly incorporated into separate Wide Area Applications. It is expected that EMS and Wide Area Applications will coexist separately for some time.

Wide-Area Measurement Systems (WAMS) are being installed on many transmission systems to supplement traditional SCADA. They measure the magnitudes and phase angle of bus-bar voltages as well as current flows through transmission circuits. This information, measured over a wide area, is transmitted to the Control Centre and it is used for:

1. *Power system state estimation*: (provides observability) Since the phasor data is synchronized, the magnitudes and phase angles of voltages at all bus bars in the grid can be estimated using a state estimation algorithm. These estimates can then be used to predict possible voltage and angle instabilities as well as to estimate system damping and vulnerability to small-signal oscillation.

2. *Power system monitoring and warning*: The phasor data allows the operating conditions of the power system to be monitored on a real-time basis, system stability to be assessed and warnings generated.

3. *Power system event analysis*: Synchronized phasor data of high accuracy is available before and after a fault or other network incident. This enables the

system operators to study the causes and effects of faults and take countermeasures against subsequent events.

1.10 Conclusion

The smart grid definition differs from community to another and there are many definitions put to describe smart grid in different ways, but all of them are talking about the intelligence and flexibility of the grid which uses advanced technologies to improve itself. This chapter discussed some general communication infrastructure installed in smart grid with the different networks (ANs); also the most features of smart grid have been discussed like smart meters and intelligence devices.

Demand side family is included also specially DSM.

As mentioned earlier smart grid proves its strength by its advanced technologies, there are various high technologies used in smart grid but in the monitoring and protection of the grid phasor measurement unit (PMU) is the most well-known tool. It allows smart grids to go far in control, maintenance and protection of the grid by its high synchronization and its high accuracy.

With the development of phasor measurement unit that has the ability to measure phasors synchronized by the GPS, power system protection has developed more and more, PMU will be taken in details in chapter 2.

Chapter 2: PMU optimal placement

2.1 Introduction

Power system operations mainly consist of data acquisitions, monitoring and controlling of the system, of which the data acquisition and monitoring play a very important role in its secure operation. Until recently, available measurement sets did not contain phase angle measurements due to the technical difficulties associated with the synchronization of measurements at remote locations. the availability of Global Positioning System (GPS) and the sampled data processing techniques developed for computer relaying applications alleviated these difficulties and lead to the development of phasor measurement unit.

Phasor Measurement Units (PMUs) have become the measurement technique of choice for electric power systems. They provide positive sequence voltage and current measurements synchronized to within a microsecond. The deployment of this device can improve performances of monitored control systems in power system protection monitoring and control.

PMU placement at all substations allows direct measurement of the state of the network. However, PMU placement on each bus of a system is difficult to achieve either due to cost factor or due to nonexistence of communication facilities in some substations, Moreover, as a consequence of Ohm’s Law, when a PMU is placed at a bus, neighboring buses also become observable This implies that a system can be made observable with a less number of PMUs than the number of buses. So it is neither economical nor necessary to install PMUs at all nodes of a wide-area interconnected network.

In recent years, many investigators presented different methods for finding the minimum number and optimal placement of PMUs in order to reach the full observability of the system. Recently the teaching-learning based optimization (TLBO) technique explained in this chapter has been used successfully in a number of N-P optimization problems.in this chapter we present a binary TLBO algorithm as a new method in order to find the minimum number of PMUs that make the system topologically observable, as well as the optimal locations of these PMUs.

2.2 Wide area monitoring, protection and control [17][8]

Wide Area Monitoring, Protection, and Control (WAMPAC) involve the use of wide area synchronized measurements, reliable and high bandwidth communication networks and advanced centralized protection and control schemes. Synchronized Measurement Technology SMT and related applications are the essential element, and enabler, of WAMPAC. Presently, Phasor Measurement Units (PMUs) are the most accurate and advanced synchronized measurement technology available. They provide voltage and current phasors and frequency information synchronized with high precision to a common time reference, the Global Positioning System (GPS). The measurement functions of a PMU are based on numerical algorithms. These algorithms must be both computationally efficient and suitable for real-time applications, particularly when the measurements are used to support dynamic-response applications.

Figure 2-1 shows the main components and structure of a generalized WAMPAC system. In this system, the necessary synchronized voltage and current phasors are produced by PMUs. The measurement data from these PMUs is transmitted through a Wide-Area Network (WAN) and aggregated at one, or more Data Concentrators (DCs).

The aggregate data is then stored locally in the DC before being transmitted to the various Application Software or Servers (ASS) of the different utilities. The main task performed by the DCs is alignment of the received PMU data; however, the opportunity also exists to perform additional pre-processing tasks before forwarding the data to ASS.

2.3 Phasor Measurement Unit

At present, phasor measurement units (PMUs) are the most accurate and advanced synchronized phasor measurement equipment. It measures 50/60 Hz sinusoidal waveforms of voltages and currents at a high sampling rate, up to 1200 samples per second and with high accuracy. From the voltage and current

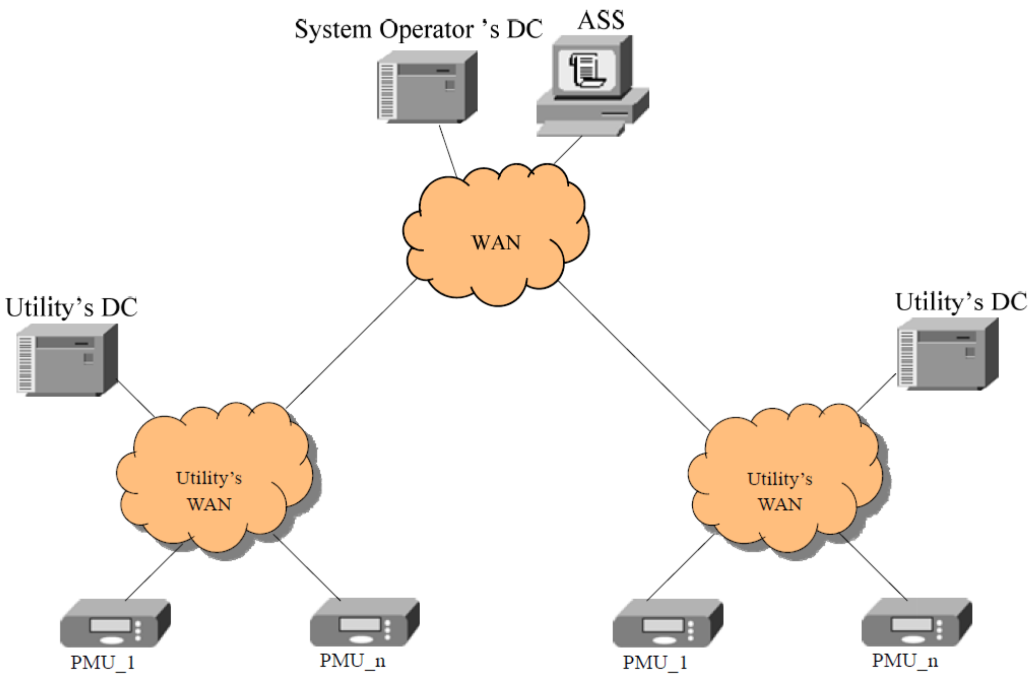


Figure 2-1 Generalized WAMPAC system [17].

samples, the magnitudes and phase angles of the voltage and current signals are calculated in the phasor microprocessor of the PMU. As the PMUs use the clock signal of the Global Positioning System (GPS) to provide synchronized phase angle measurements at all their measurement points, the measured phasors are often referred to as synchrophasors

Figure 2-2 gives a functional block diagram of a typical PMU. The GPS receiver provides the 1 pulse-per-second (pps) signal, and a time tag consisting of the year, day, hour, minute, and second. The l-pps signal is usually divided by a phase-locked oscillator into the number of pulses per second required for the sampling of the analogue signals. The analogue signals are derived from three-phase voltage and current transformers with appropriate anti-aliasing filtering. The microprocessor calculates the positive sequence voltage and current phasors, and determines the timing message from the GPS, along with the sample number at the beginning of a window.

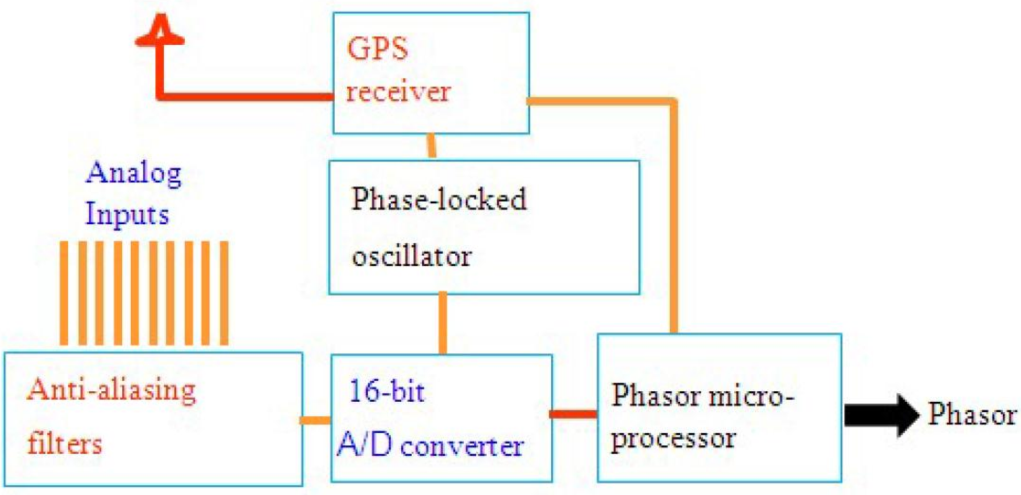


Figure 2-2 A functional block diagram of a typical PMU[18].

Figure 2-3 compares the voltage angle difference between two substations obtained using PMU measurements and traditional state estimation. This comparison demonstrates clearly that a real time monitoring system made up of PMUs will provide much more precise and dynamic system operation information than the traditional state estimation.

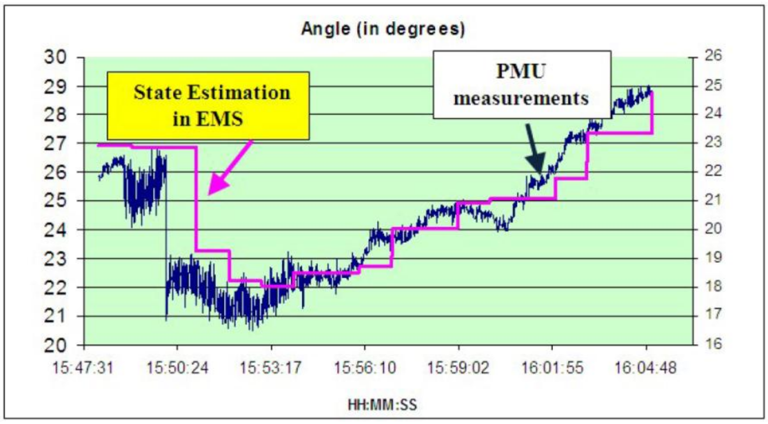


Figure 2-3 State estimation vs. PMU measurements [9].

The algorithms behind phasor measurement date back to the development of symmetrical Component Distance Relays (SCDR) in the 1970's. The major breakthrough of SCDR was its ability to calculate symmetric positive sequence voltage and current using a recursive Discrete Fourier Transform. The sampling process is described in Figure 2-4. The recursive algorithm continually updates the sample data array by including the newest sample and removing the oldest sample to produce a constant phasor.

$$X = X_r + jX_i = \frac{\sqrt{2}}{N}\sum_{k=1}^{N}(x_k \cos\frac{2\pi k}{N} - j x_k \cos\frac{2\pi k}{N})$$

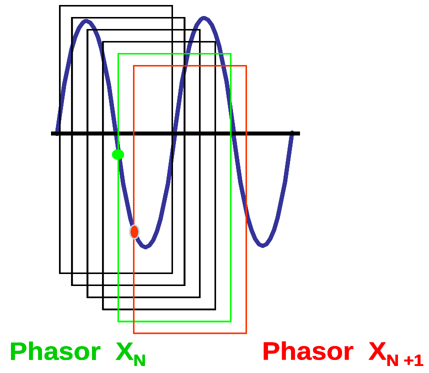


Figure 2-4 Sampling Process of first PMU algorithms [19].

The advent of the Global Positioning System (GPS) in the 1980’s was the second breakthrough that enabled the modern PMU. Researchers at Virginia Tech’s Power Systems Laboratory in the mid 1980’s were able to use the pulses from the GPS satellites to synchronize and time stamp the phasor data with an accuracy of 1.0 µs. With the addition of effective communication and data collection systems, voltage and current phasors from different locations could be compared in real-time[20].

2.4 Hierarchy for PMU-based power protection systems

Such systems comprise a number of Phasor Measurement Units (PMU) and a central evaluation unit which resides in a system protection center. The PMUs are installed at strategic sub-stations throughout the power system. The selection of sub-stations where these installations take place depends upon the use to be made and the measurements they provide. The optimal placement of PMUs will be considered in next sections. In most applications, the phasor data is used at locations remote from the PMUs. Thus an architecture involving PMUs, communication links, and data concentrators (in system protection center) must exist in order to realize the full benefit of the PMU measurement system (wide area monitoring and protection systems)[21].

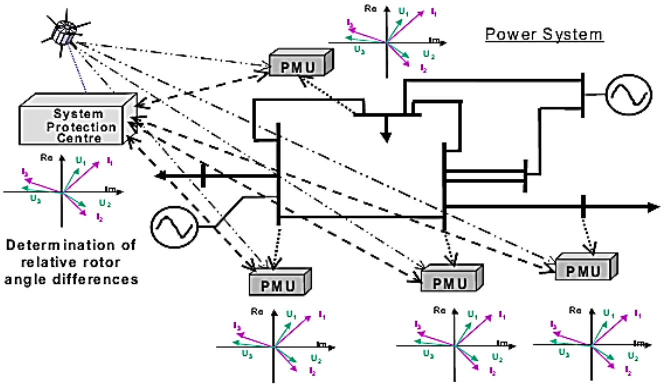


Figure 2-5 PMUs in wide area monitoring and control systems [22].

2.5 Fundamentals of PMU

A pure sinusoidal waveform can be represented by a unique complex number known as a phasor. Consider a sinusoidal signal[23]:

$$\boldsymbol{x(t) = X_m \cos(\omega t + \varphi)} \tag{2-1}$$

The phasor representation of this sinusoidal is given by:

$$\boldsymbol{x(t) = \frac{X_m}{\sqrt{2}} e^{j\varphi} = \frac{X_m}{\sqrt{2}} (\cos(\varphi) + j\sin(\varphi))} \tag{2-2}$$

The signal frequency ω is not explicitly stated in the phasor representation. The term$e^{j\omega}$ is customary suppressed in the expression above, with the understanding that the frequency is ω. The magnitude of the phasor is the rms value of the sinusoid $\frac{\mathrm{Xm}}{\sqrt{2}}$ and its phase angle is φ, the phase angle of the signal in (2-1) [24]. The sinusoidal signal and its phasor representation given by (2-1) and (2-2) are illustrated in Figure 2-6.

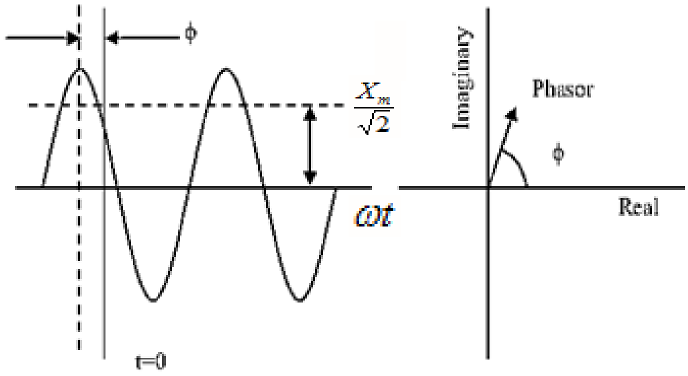


Figure 2-6 Phasor representation [21].

Sinusoidal signal (left) Sinusoidal signal, (right) Phasor representation.

2.6 The Optimal Placement Problem

PMUs provide two types of measurements: bus voltage phasors and branch current phasors. Depending on the type of PMUs the number of channels used for measuring voltage and current phasors will vary. Here, it is assumed that each PMU has enough channels to record the bus voltage phasor at its associated bus and current phasors along all branches that are incident to this bus. Since GPS provides negligible synchronization error, the interests are concentrated on where and how many PMUs should be implemented in a power system with the smallest cost and with the largest degree of observability, hence The prerequisite for an efficient and accurate control is the development of adequate meter placement scheme, which can realize the network full observability.

The PMU Placement Optimization (OPP) is to minimize the number of PMUs by optimizing the PMU's locations, while keeping all the nodes voltage phasors observable. An example of an optimally placed set of PMUs in a 14-bus system is shown below in Figure 2-7.

In this system, there are three PMUs placed at buses 2, 6 and 9 respectively. Bus 7 is the only zero injection bus. The PMU at bus 2 can not only measure the voltage phasor of bus 2, but also the current phasors of branches 2-1, 2-3, 2-4 and 2-5.Using Ohm's law, the voltage phasors at buses 1, 3, 4 and 5 can be obtained as:

$V_2, I_{2,1}, I_{2,3}, I_{2,4}\ and\ I_{2,5}$ are all known as well as impedances of any line, using Ohm's law:

$$V_1 = V_2 - I_{2,1} \times Z_{2,1}$$

$$V_3 = V_2 - I_{2,3} \times Z_{2,3}$$

$$V_4 = V_2 - I_{2,4} \times Z_{2,4}$$

$$V_5 = V_2 - I_{2,5} \times Z_{2,5}$$

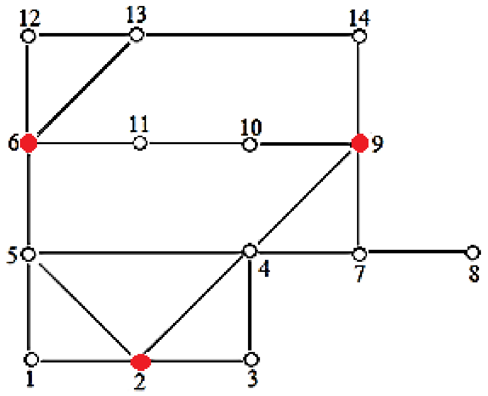


Figure 2-7 IEEE 14-bus system with 3 PMUs [23].

currents and the voltage at bus 2. The buses states around bus 6 can be found in a similar way. Now the states around bus 9:

$V_9, I_{9,4}, I_{9,7}, I_{9,14}$ and $I_{9,10}$ are all known as well as impedances:

$$V_{10} = V_9 - I_{9,10} \times Z_{9,10}$$

$$V_4 = V_9 - I_{9,4} \times Z_{9,4}$$

$$V_{14} = V_9 - I_{9,14} \times Z_{9,14}$$

Since V_7 is an injection bus, using the Kirchhoff's Current Law:

$$I_{4,7} + I_{9.7} + I_{8,7} = 0 \Rightarrow I_{8,7} = -I_{4,7} - I_{9.7} \Rightarrow V_8 = -I_{8,7} \times Z_{8,7}$$

Hence bus 8 is observable.

Thus the entire system becomes observable by placing only three PMUs at buses 2, 6, 9 and by considering the zero injection at bus 7.

In the following sections, the procedure to solve the PMU placement problem is introduced. This method will be discussed in detail via the use of the IEEE 14-bus as an example in the following sections.

2.6.1 Observability Analysis

a. Observability

Observability is a fundamental component of many applications in power system protection such as real-time state estimation. Observability of electric power system is to study whether there is enough measurement in system in order to measure the state of electric power system including the amplitude value of the voltage and current as well as the phase angle between them.

Power system observability might be defined by graph theory. An N-bus power system is represented as a graph G= (V, E), where V is a set of graph vertices containing all system buses, and E is a set of graph edges containing all system branches [29]. Before developing the rules of observability, a definition of flow and injection measurements might be necessary.

Injection is a variable load or source so that an injected current is supplied to the bus. Zero injection buses are the buses from which no current is being injected into the system [25]. Flow measurements are those measurements taken from some power system instruments and allow the calculation of line current magnitude and power flowing (real/reactive) through the line where they are installed. So having these measurements help in reducing the total number of PMUs for complete observability of the system.

b. Observability rules for the optimal placement problem:

Totally observability is divided by numerical and topological states. For the present work we use observability topology analysis method based on PMUs according to observability rules below [29]:

- **Rule 1**: If a PMU is placed at a bus, this bus and its entire neighbor buses can be observed as shown in Figure 2-8-a
- **Rule 2**: For a zero injection node which is observed, if all of its connected nodes are observable except one, then the unobserved node can be observed (Figure 2-8-b);
- **Rule 3**: If all the nodes connected a zero injection node are observable, then the zero injection node can be observed too, as depicted in Figure 2-8-c

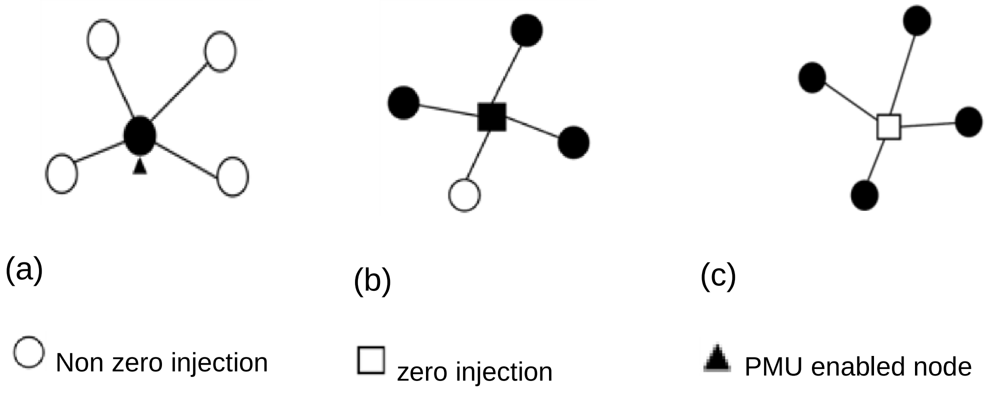


Figure 2-8 Topological Observability Rules based on PMU [25].

2.6.2 Problem Formulation

A numerical method will be presented her to solve the problem. The formulation used is explained below.

For an n-bus system, the PMU placement problem can be formulated as follows:

$$\text{Objective function(J)} \;\; = Min \sum_{i}^{n} x_i$$
$$\text{Such that} \quad f\,(X) \geq \hat{\imath} \qquad (2\text{-}3)$$

Where X is a binary decision variable vector, in which each entry x_i is defined as:

$$x_i = \begin{cases} 1 & \text{if Bus } i \text{ has a PMU} \\ 0 & \text{otherwise} \end{cases} \qquad (2\text{-}4)$$

f (X) is a vector function, whose entries are non-zero if the corresponding bus voltage is solvable using the given measurement set and zero otherwise.

î is a vector whose entries are all ones [25].

2.6.3 Constraints

In order to form the constraint set, the binary connectivity matrix A will be formed first [30]. Each entry A_{km} from it is defined as:

$$A_{km} = \begin{cases} 1 & k = m \\ 1 & k \text{ and } m \text{ connected} \\ 0 & \text{otherwise} \end{cases} \qquad (2\text{-}5)$$

Based on the acknowledgement that by placing a PMU on one bus, the voltage phasors of this bus and its neighboring buses can be calculated, we can get

$$f = A \times X \tag{2-6}$$

Constraint functions defined by equations (2-3) ensure full network observability while minimizing the total number of the PMUs.

The procedure for building the constraint equations (vector function *f (X)*) will be presented for four possible cases:

- No PMU measurements or conventional(flow and injection) measurements exist
- Only flow measurements exist,
- Both flow and injection measurements (they may be zero injections or measured injections) exist or
- PMU measurements and conventional flow or injection measurements exist.

The procedure for each case will be described using IEEE 14-bus system as an example.

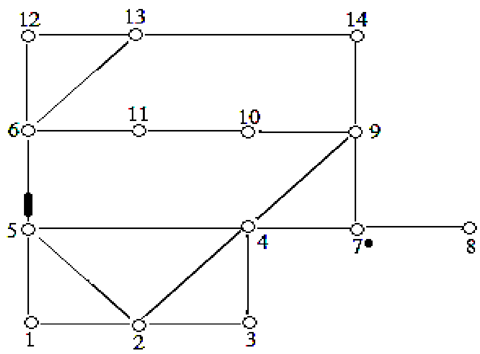


Figure 2-9 IEEE 14-bus system with conventional measurements [26].

Consider the IEEE 14-bus system and its measurement configuration shown in Figure 2-9. In this system, there is a conventional paired flow measurement on line 5-6, which is represented by a black box, and a PMU measurement at bus 10. Also, note that bus 7 is a zero injection bus which is indicated by the black dot next to it. Building the A matrix for the 14-bus system by following equation (2-6) yields:

For bus 1, it is connected to 2 and 5 therefore the 1st , 2nd and 5th elements in the first row is 1, the rest are all 0.

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \tag{2-7}$$

<u>Case 1: A system with no PMUs or conventional measurements</u>

In this case, the PMU, the flow and the injection measurements are ignored. In order to make all bus voltage phasors solvable for this case, the following inequality constraints should be satisfied:

$$f(X) = \begin{cases} f_1 = x_1 + x_2 + x_5 & \geq 1 \\ f_2 = x_1 + x_2 + x_3 + x_4 + x_5 & \geq 1 \\ f_3 = x_2 + x_3 + x_4 & \geq 1 \\ f_4 = x_2 + x_3 + x_4 + x_5 + x_7 + x_9 & \geq 1 \\ f_5 = x_1 + x_2 + x_4 + x_5 + x_6 & \geq 1 \\ f_6 = x_5 + x_6 + x_{11} + x_{12} + x_{13} & \geq 1 \\ f_7 = x_4 + x_7 + x_8 + x_9 & \geq 1 \\ f_8 = x_7 + x_8 & \geq 1 \\ f_9 = x_4 + x_7 + x_9 + x_{10} + x_{14} & \geq 1 \\ f_{10} = x_9 + x_{10} + x_{11} & \geq 1 \\ f_{11} = x_6 + x_{10} + x_{11} & \geq 1 \\ f_{12} = x_6 + x_{12} + x_{13} & \geq 1 \\ f_{13} = x_6 + x_{12} + x_{13} + x_{14} & \geq 1 \\ f_{14} = x_9 + x_{13} + x_{14} & \geq 1 \end{cases} \tag{2-8}$$

The operator ”+” serves as the logical ”OR” and the use of ”1” in the right hand side of the inequality ensures that at least one of the variables appearing in the sum will be non-zero. For example, consider the constraint associated with bus 1 as given below:

$f_1 = x_1 + x_2 + x_5 \geq 1$

It implies that at least one PMU must be placed at either one of buses 1, 2 or 5 in order to make bus 1 observable. Similarly, the second constraint implies that one PMU should be installed at any of the buses 1, 2, 3, 4, or 5 in order to make bus 2 observable. The same thing is applied for all the constraints.

Case 2: A system with some flow measurements

This case considers the situation where some flow measurements may be present. Flow measurement on branch 5-6 in the 14-bus example system will be used to illustrate the approach on how to deal with existing flow measurements. Existence of this flow measurement will lead to the modification of the constraints for buses 5 and 6 accordingly. Modification follows the observation that having a flow measurement along a given branch allows the calculation of one of the terminal bus voltage phasors when the other one is known. Hence, the constraint equations associated with the terminal buses of the measured branch can be merged into a single constraint. In the case of the example system, the constraints for buses 5 and 6 are merged into a joint constraint as follows,

$$\begin{gathered}\begin{cases} f_5 = x_1 + x_2 + x_4 + x_5 + x_6 & \geq \quad 1 \\ f_6 = x_5 + x_6 + x_{11} + x_{12} + x_{13} & \geq \quad 1 \end{cases} \Rightarrow \\ f_{5,new=} f_5 + f_6 = x_1 + x_2 + x_4 + x_5 + x_6 + x_{11} + x_{12} + x_{13} \geq 1 \end{gathered} \tag{2-9}$$

Which implies that if either one of the voltage phasors at bus 5 or 6 is observable, the other one will be observable. Applying this modification to the constraints for the 14-bus system, the following set of constraints will be obtained,

$$f(X) = \begin{cases} f_1 = x_1 + x_2 + x_5 & \geq 1 \\ f_2 = x_1 + x_2 + x_3 + x_4 + x_5 & \geq 1 \\ f_3 = x_2 + x_3 + x_4 & \geq 1 \\ f_4 = x_2 + x_3 + x_4 + x_5 + x_7 + x_9 & \geq 1 \\ f_{5\_new} = x_1 + x_2 + x_4 + x_5 + x_6 + x_{11} + x_{12} + x_{13} & \geq 1 \\ f_7 = x_4 + x_7 + x_8 + x_9 & \geq 1 \\ f_8 = x_7 + x_8 & \geq 1 \\ f_9 = x_4 + x_7 + x_9 + x_{10} + x_{14} & \geq 1 \\ f_{10} = x_9 + x_{10} + x_{11} & \geq 1 \\ f_{11} = x_6 + x_{10} + x_{11} & \geq 1 \\ f_{12} = x_6 + x_{12} + x_{13} & \geq 1 \\ f_{13} = x_6 + x_{12} + x_{13} + x_{14} & \geq 1 \\ f_{14} = x_9 + x_{13} + x_{14} & \geq 1 \end{cases} \quad (2\text{-}10)$$

Case 3: A system with both injection measurements (some of which may be zero injection measurements) and flow measurements

In this case, injection measurements whether they are real measurements or zero injections, are treated the same way. Consider again the same 14-bus system, where bus 7 is a zero injection bus. It is easy to see that if the phasor voltages at any three out of the four buses 4, 7, 8 and 9 are known, then the fourth one can be calculated using the Kirchhoff's Current Law applied at bus 7 where the net injected current is known.

The following method is developed for systems with a relatively large number of injections. An approach involving a topology transformation which is used for our work will be discussed next.

2.6.4 Topology transformation

This alternative method referred here as the topology transformation is developed for handling injection measurements. The main idea is to merge the bus which has the injection measurement, with any one of its neighbors. This is based on the observation that if the voltage phasors of all its neighbors are known, the voltage phasor of this injection bus can be calculated by the Kirchhoff's Current Law.

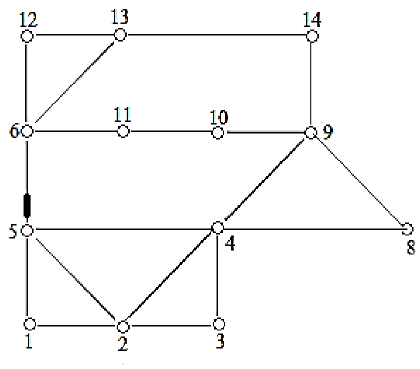


Figure 2-10 Topology transformation applied on IEEE 14-bus system [26].

Figure 2-10 shows the updated system diagram after the merger of buses 7 and 8 into a new bus 8'. The newly created branch 8' − 9 reflects the original connection between buses 7 and 9[25]. Hence, the constraints vector function can be formed as shown in equation (2-10).

$$f(X) = \begin{cases} f_1 = x_1 + x_2 + x_5 & \geq 1 \\ f_2 = x_1 + x_2 + x_3 + x_4 + x_5 & \geq 1 \\ f_3 = x_2 + x_3 + x_4 & \geq 1 \\ f_4 = x_2 + x_3 + x_4 + x_5 + x_{8'} + x_9 & \geq 1 \\ f_{5\_new} = x_1 + x_2 + x_4 + x_5 + x_6 + x_{11} + x_{12} + x_{13} & \geq 1 \\ f_{8'} = x_4 + x_{8'} + x_9 & \geq 1 \\ f_9 = x_4 + x_{8'} + x_9 + x_{10} + x_{14} & \geq 1 \\ f_{10} = x_9 + x_{10} + x_{11} & \geq 1 \\ f_{11} = x_6 + x_{10} + x_{11} & \geq 1 \\ f_{12} = x_6 + x_{12} + x_{13} & \geq 1 \\ f_{13} = x_6 + x_{12} + x_{13} + x_{14} & \geq 1 \\ f_{14} = x_9 + x_{13} + x_{14} & \geq 1 \end{cases} \quad (2\text{-}11)$$

Yet a word of caution needs to be added here in that, if the optimal solution chooses the newly formed fictitious bus (merger of two actual buses) as a candidate bus, it may indicate to place one PMU on one of these two buses or two PMUs on both. In this case, a topology analysis needs to be applied to check the observability of the system. This also assures that the minimum number of PMUs will be placed.

Case 4: A system with flow, injection, and PMU measurements

This case considers the most general situation where both conventional flow or injection measurements and PMU measurements may be present, but not enough to make the entire system observable. To build the constraints for this case is simple. After forming the constraint equation *f(X)* according to the procedure described above, simply replace all the x_i by 1, where *i* represents the bus with an already installed PMU [23].

Consider again the 14-bus system shown in Figure 1-10. There is a PMU installed at bus 10, all x_{10} terms appearing in the constraint set in Equations (2-10) will have to be replaced by 1. The modified equations in Equation (2.10) will look as follows:

$$f_9 = x_4 + x_8 + x_9 + x_{10} + x_{14} = 1 \tag{2-12}$$

$$f_{10} = x_9 + x_{10} + x_{11} = 1 \tag{2-13}$$

$$f_{11} = x_6 + x_{10} + x_{11} = 1 \tag{2-14}$$

Now that f_9, f_{10} and f_{11} are all ones, they can be removed from the constraint equations, Equation (2.10) will be modified as:

$$f(X) = \begin{cases} f_1 = x_1 + x_2 + x_5 & \geq 1 \\ f_2 = x_1 + x_2 + x_3 + x_4 + x_5 & \geq 1 \\ f_3 = x_2 + x_3 + x_4 & \geq 1 \\ f_4 = x_2 + x_3 + x_4 + x_5 + x_{8'} + x_9 & \geq 1 \\ f_{5\_new} = x_1 + x_2 + x_4 + x_5 + x_6 + x_{11} + x_{12} + x_{13} & \geq 1 \\ f_{8'} = x_4 + x_{8'} + x_9 & \geq 1 \\ f_{12} = x_6 + x_{12} + x_{13} & \geq 1 \\ f_{13} = x_6 + x_{12} + x_{13} + x_{14} & \geq 1 \\ f_{14} = x_9 + x_{13} + x_{14} & \geq 1 \end{cases} \tag{2-15}$$

2.7 The Teaching–learning-based-optimization

2.7.1 Mechanism of TLBO:

Most of the metaheuristic methods are inspired from nature i.e. they mimic the behavior of nature. For example Genetic Algorithm is inspired from Darwin's theory, the strongest is the one who survive, Particle swarm is inspired from the movement of a flock of bird, a school of fish, or a swarm of bees that are looking for food, Artificial Bee Colony (ABC) simulates the intelligent forging of honey bee swarm, Ant colony shows how ants search for food and how to find an optimal way to it,…etc. They prove their effectiveness in solving many engineering optimization problems but each one of them requires its own algorithm specific control parameters. For example, Genetic Algorithm (GA) uses mutation rate and crossover rate. Similarly ¨Particle Swarm Optimization (PSO) uses inertia weight, social and cognitive parameters. The improper tuning of algorithm specific parameters either increases the computational effort or yields the local optimal solution. Considering this fact, recently Rao et al. (2011, 2012), Rao & Savsani (2012) and Rao & Patel (2012) introduced the Teaching-Learning Based Optimization (TLBO) algorithm which does not require any algorithm specific parameters. In this way TLBO obtain global solutions for continuous nonlinear functions with less computational effort and high consistency [58].

TLBO is a teaching-learning process inspired algorithm based on the effect or influence of a teacher on the output of learners in a class. Teacher and learners are the two vital components of the algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). The output in TLBO algorithm is considered in terms of results or grades of the learners which depend on the quality of teacher. So, teacher is usually considered as a highly learned person who trains learners so that they can have better results in terms of their marks or grades. Moreover, learners also learn from the interaction among themselves which also helps in improving their results [58].

TLBO is a population based method. In this optimization algorithm a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and learners result is analogous to the ‘fitness’ value of the optimization problem. In the entire population the best solution is considered as the teacher. The working of TLBO is divided into two parts, ‘Teacher phase’ and ‘Learner phase’. Working of both the phases is explained below.

<u>Teacher phase:</u> in this phase the best student is chosen from the population (the class) according to the fitness function and set as a teacher. Since the teacher is the highest learned person in the class, he puts effort to disseminate knowledge among students so that he tries to bring the mean level of the class up to his level, the new mean of the class depends on two things:

- The ability of the teacher i.e. his method in teaching is good or bad and this is represented by a factor t_f called “teaching factor”, it can be 1 or 2 (those values are concluded from experiments by the inventors of TLBO).
- The ability of the student to receive and understand concepts from his teacher.

Learner phase: as known, when a student does not understand his teacher or he wants to have more knowledge, he will interact with one of their fellow students. If he finds his friend better than himself he will learn from him otherwise he will not [58].

2.7.2 Implementation of TLBO Algorithm for optimization:

TLBO can be implemented in five steps:

Step1: formulate the optimization problem, the objective function and the side constraints:

Minimize (objective function) $y = f(x_1, x_2, \ldots., x_{n-1}, x_n)$such that:

$x_j^{min} \leq x_j \leq x_j^{max}$ Where j=1, 2, 3,……,D those are the side constraint which specify the limit of each design variable i.e. the maximum and minimum level in each course of any student.

The variables $x_1, x_2, \ldots., x_{n-1}, x_n$ represent the level of student $\mathbf{X}$ in each course so x_1 is the level of $\mathbf{X}$ in the first course.

Decide how many students will be used or the population size, also the number of generation. Here a minimization problem is considered; the maximization is similar.

Step 2: initialization: suggest a population (that will be developed to reach the final solution) or students randomly according to the following equation:

$$\boldsymbol{x}_{(i,j)}^{\boldsymbol{1}} = \boldsymbol{x}_j^{\boldsymbol{min}} + \boldsymbol{rand}_{(i,j)} \times (\boldsymbol{x}_j^{\boldsymbol{max}} - \boldsymbol{x}_j^{\boldsymbol{min}}) \quad (2\text{-}16)$$

i:refers to student number, so this is the ith student, *i*=1, 2, …,P

j:refers to the course number.

$x_{(i,j)}$ is the level of the ith student at the jth course, *j*=1, 2,…,D

The small number 1 refer to the generation number, it’s the first generation.

After manipulating the above equation $P \times D$ times, a $P \times D$ matrix which represents the population is obtained:

$$\boldsymbol{population^1} = \begin{bmatrix} \boldsymbol{x^1_{(1,1)}} & \cdots & \boldsymbol{x^1_{(1,D)}} \\ \boldsymbol{x^1_{(2,1)}} & & \boldsymbol{x^1_{(2,D)}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x^1_{(P,1)}} & \cdots & \boldsymbol{x^1_{(P,D)}} \end{bmatrix} \quad (2\text{-}17)$$

So $X_1^1 = (x^1_{(1,1)},\ x^1_{(1,2)}, \ldots, x^1_{(1,D)})$ is student number 1 in the first generation.

Choose the teacher: the best student is the one which has the minimum fitness function.

Step 3: teacher phase

Calculate the mean in each column in the population matrix:

$$\boldsymbol{mean^g} = \begin{bmatrix} \boldsymbol{mean}(\boldsymbol{x^g_{(1,1)}}, \boldsymbol{x^g_{(2,1)}}, \ldots, \boldsymbol{x^g_{(p,1)}}) \\ \boldsymbol{mean}(\boldsymbol{x^g_{(1,2)}}, \boldsymbol{x^g_{(2,2)}}, \ldots, \boldsymbol{x^g_{(p,2)}}) \\ \vdots \\ \boldsymbol{mean}(\boldsymbol{x^g_{(1,D-1)}}, \boldsymbol{x^g_{(2,D-1)}}, \ldots, \boldsymbol{x^g_{(p,D-1)}}) \\ \boldsymbol{mean}(\boldsymbol{x^g_{(1,D)}}, \boldsymbol{x^g_{(2,D)}}, \ldots, \boldsymbol{x^g_{(p,D)}}) \end{bmatrix} \quad (2\text{-}18)$$

Mathematically, how the best student teaches the others:

$$X_{i,new} = X_i + (X_{teacher} - t_f \times mean) \quad (2\text{-}19)$$

t_f is the teaching factor, it can be 1 or 2.

A comparison between the new student $X_{i,new}$ and the old one X_i should be made, if $X_{i,new}$ is better than X_i, replace the old by the new one otherwise keep the old one.

$$if\ f\left(X_{i,new}\right) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing$$
$$i = 1, 2, \ldots, P. \quad (2\text{-}20)$$

Step 4: learner phase

This phase shows the interaction between students.

For each student i we pick another student j randomly and compare their level (fitness function), the first student i will learn from the second j (get close to him) if he is better than him otherwise he will go far from him, according to the formula:

$$X_{i,new}^{g} = \begin{cases} X_i^g + rand_i^g \times \left(X_j^g - X_i^g\right), & if\ f\left(X_i^g\right) > f(X_j^g)\ \ better \\ X_i^g + rand_i^g \times \left(X_i^g - X_j^g\right), & if\ f\left(X_i^g\right) \leq f(X_j^g)\ \ worst \end{cases} \quad (2\text{-}21)$$

$$if\ f\left(X_{i,new}\right) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing$$

After completing the process for all the population, the fittest student is set as teacher.

Step 5: if $g \neq number\ of\ generation$ go to step 3 else stop.

The flowchart of the TLBO algorithm is shown in Figure 1-12.

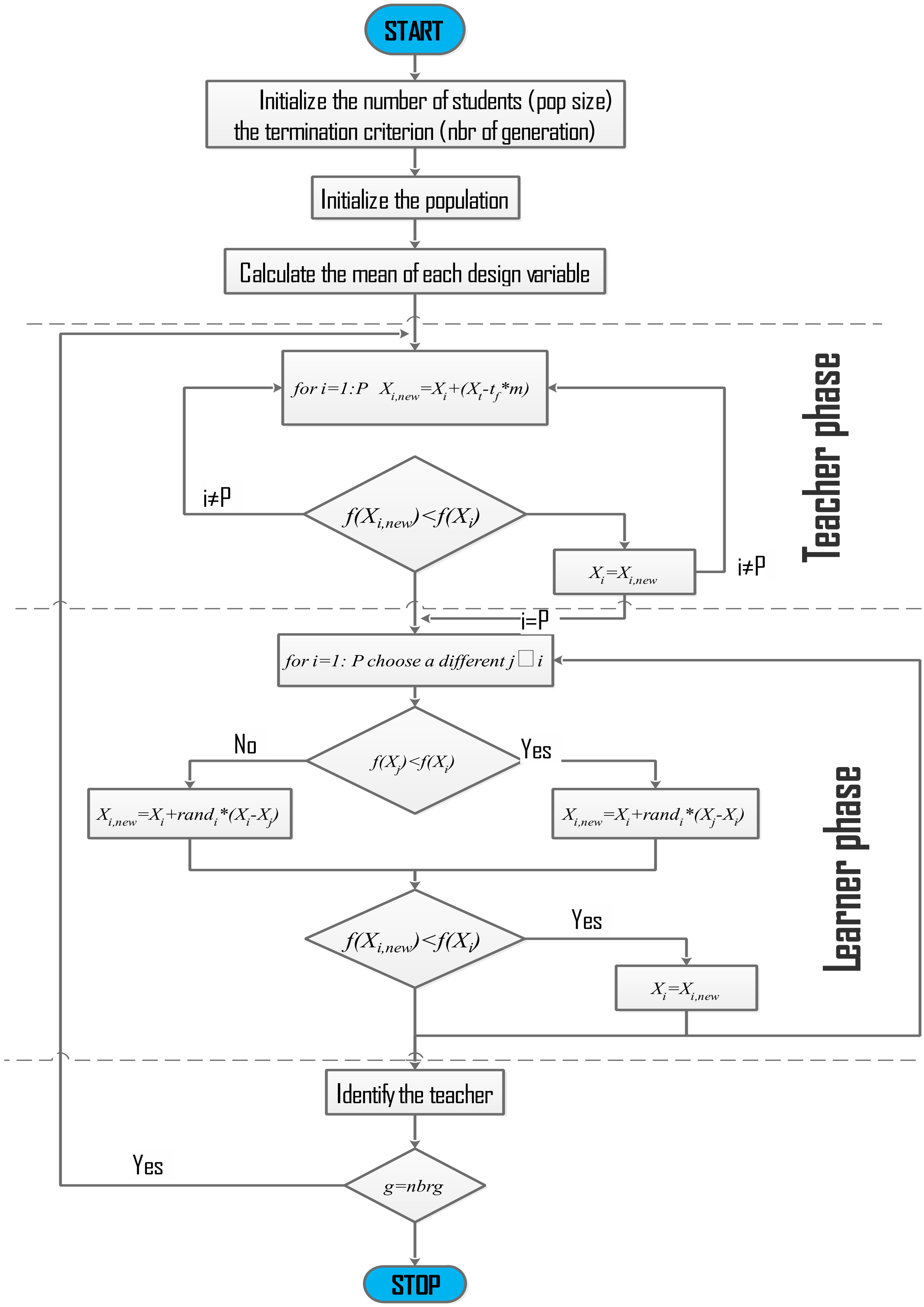


Figure 2-11 Flowchart of TLBO Algorithm.

2.8 Elitist teaching-learning-based optimization

The concept of elitism is used in most population based algorithm where worst solutions are replaced by elite solutions, and the effect of this process can easily explained: a population which has better elements than another one can get a better solution, in language of the TLBO, a class with good student will have a good level so definitely that class will reach the optimal solution quickly. Also the concept of elitism includes removing duplicate solutions to make the class has distinct students.

After implementing teacher and learner phases, a verification of no two similar students is made. If they exist, one of them will be modified by mutation keeping the constraints satisfied.

The worst solutions will be replaced by elite ones. The number of bad solutions which will be replaced by elite solutions is controlled by the elite size[26]. Figure 2-12 illustrates how to remove duplicate solutions and bad students, that procedure should be applied in the main TLBO after the learner phase and it should be followed by a “Remove duplicate solutions box”.

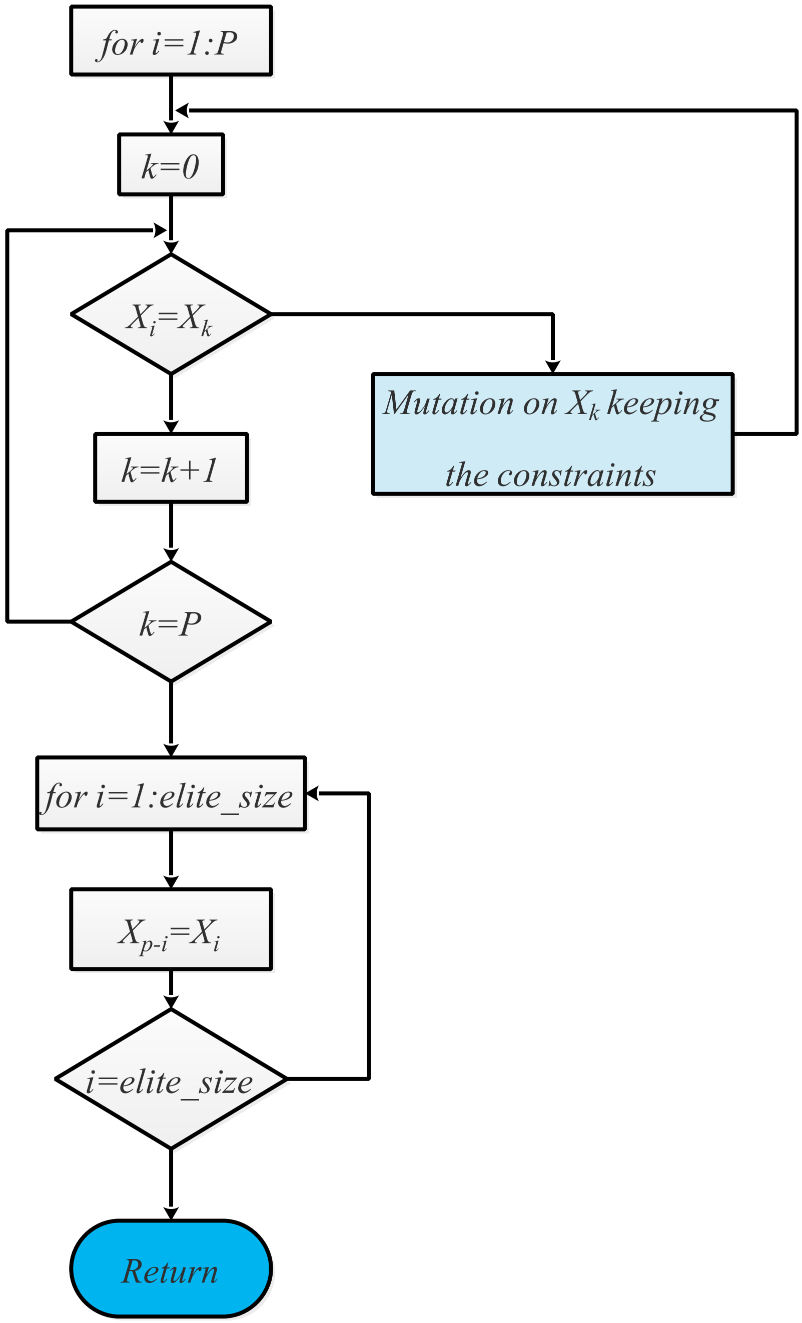


Figure 2-12 Flowchart of elitist procedure.

2.9 The proposed binary version of the TLBO (BTLBO)

The TLBO does not have a binary version for solving the OPP of PMU since it is a new method; a binary version for it has been proposed in this section. The difficulty is how to change equations (2-19) and (2-21) to be valid for binary vectors.

The algorithm in binary can be performed through:

Step 0: define the optimization problem, the objective function:

Minimize (objective function) $y = f(x_1, x_2, \ldots., x_{n-1}, x_n)$ such that: $x_1, x_2, \ldots., x_{n-1}, x_n$ can take only two values: either a 1 or a 0.

Decide how many students will be used or the population size, elite size and the number of generation.

Step 1: initialization: suggest a population (that will be developed to reach the final solution) or students randomly according to the following equation:

$$x^1_{(i,j)} = randi([0,1], 1) \tag{2-22}$$

i:refers to student number, so this is the ith student, *i*=1, 2, …,P

j:refers to the course number, $x_{(i,j)}$ is the level of the ith student at the jth course, *j*=1, 2,…,D

The small number 1 refers to the generation number, it's the first generation.

After manipulating the above equation $P \times D$ times, a $P \times D$matrix is obtained:

$$\boldsymbol{population^1} = \begin{bmatrix} \boldsymbol{x^1_{(1,1)}} & \cdots & \boldsymbol{x^1_{(1,D)}} \\ \boldsymbol{x^1_{(2,1)}} & & \boldsymbol{x^1_{(2,D)}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x^1_{(P,1)}} & \cdots & \boldsymbol{x^1_{(P,D)}} \end{bmatrix} \tag{2-23}$$

Choose the teacher: the best student is the one which has the minimum fitness function.

Step 2: teacher phase

As in real version each student tries to be like his teacher, so he makes his design variables as those of the teacher, of course not all of them otherwise he will be identical to his teacher, so the student copies some components of teacher and replace his components by those copied ones. The number of copied components depends on the ability of teacher and the student; this is represented by one random number h that ranges between 0 and D. The corresponding formula is:

$$h = randi(D, 1) \tag{2-24}$$

This number determines how many courses that student i will learn from his teacher.

The location of those courses in the teacher vector can be specified according to the equation below:

$$course = randi(h, [1, h]) \tag{2-25}$$

These randomly selected courses are now ready to be transmitted from teacher to student:

$$\begin{aligned}
&X_{i,new} = X_i \\
&X_{i,new}(course) = X_{Teacher}(course) \qquad (2\text{-}26) \\
&if\ f\left(X_{i,new}\right) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing
\end{aligned}$$

Executing (2-26) may produce duplicate solutions; therefore an additional step is needed.

Step 3: remove duplicate solutions by mutation on randomly selected dimensions.

Step 4: learner phase

The interaction between students in binary search space will be as follows:

choose for a student i another one j, if j is better than i then i will learn from j by trying to change components that are different from those of j, in order to be like him; otherwise he will change some components that are similar to those of j. This can be done as follows:

$$For\ i = 1{:}P\ do$$

Choose another student j and record where they are similar and where they are different in a vector

$$\boldsymbol{q} = [q_1\ q_2\ \ldots\ldots\ldots q_D] \text{ such that } q_k = 1\ if\ x_{i,k}^g = x_{j,k}^g \text{ else } q_k = 0;\quad k = 1, \ldots, D$$

The vector $h = randi(D, 1)$ specifies how many courses will student i learn from j if he is better than him or change them in other case.
The vector $course = randi(h, [1, h])$ specifies the location of courses which will be learnt or changed.

Now the learning process can be implemented:

$X_{i,new} = X_i$ The new student is the old with some modifications.

$$if\ f(X_i^g) > f(X_j^g)\ then\ X_{i,new}\ (course) = X_j\ (course).*\ not(\boldsymbol{q}(course))$$
$$else\ f(X_i^g) \le f(X_j^g)\ then\ X_{i,new}\ (course) = not(X_j\ (course)).*\ q(course) \quad (2\text{-}27)$$

(2-27) says that some components where i and j differ will be copied from j (the highest learned one between the two) to i otherwise (j is worse than i) some of similar components in i will be reversed from 0 to 1 or 1 to 0. Now, check if the new student is better than the old:

$$if\ f(X_{i,new}) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing \quad (2\text{-}28)$$

After completing the process for all the population, a new teacher will be determined.

Step 5: Remove duplicate solutions and bad ones and again remove duplication.

Step 6: if $g \neq number\ of\ generation$ go to *step2 else stop.*

Different experiments have been conducted to check the effectiveness of binary TLBO. Some examples are investigated based on benchmark test functions (see Appendix). The table below shows the obtained results:

Table 2.1 experimental results of binary TLBO

Benchmark function	Ackley	Grienwank	Rosenbrock	Sphere
Variables	10	10	10	10
Binary bits	4	4	4	4
Ranges	$-2 \leq x_i \leq 2$	$-2 \leq x_i \leq 2$	$-2 \leq x_i \leq 2$	$-2 \leq x_i \leq 2$
Generations	50	40	150	80
Pop_size	30	25	60	30
Real Solution	[0 … 0]	[0 … 0]	[1 1 …1]	[0 0 …0]
Obtained solution	[0 … 0]	[0 … 0]	[1 1 …1]	[0 0 …0]

2.10 Binary Teaching-Learning Based Optimization (BTLBO) For OPP of PMU

Using the binary teaching learning based optimization explained in section(2.9) and based on the problem formulation pointed out in section (2.6) ; an algorithm for the optimal placement problem is developed below:

1. Built the binary connectivity matrix using the one line diagram and constraint modification when injection, flow measurements or already installed PMUs exist.
2. Define the optimization parameters; the population size (Pop_size), the design variables (N_buses), and the number of generation (N_gen), the elite size (elite_size).
3. Generate random solutions within boundaries of the system.
4. Check that random solutions satisfy the inequality constraint of buses

   f(x)=(A*X) ≥ î, modify those not satisfying the constraints.
5. Calculate the fitness of each solution based on the objective function of expression (2-3)
6. Set the best solution as a teacher of the population.
7. For each student apply teacher phase, replace x by x_{new} if it gives better fitness function (less) otherwise keep the old one.

8. If the duplicate solutions exist then it is necessary to modify the duplicate solutions in order to avoid trapping in local optima. In the present work, duplicate solutions are modified by mutation on randomly selected dimensions of the duplicate solutions before executing the next generation without losing the observability.
9. For each student apply learner phase, replace x by x_{new} if it gives better fitness function (less) otherwise keep the old one.
10. Again, remove duplicate solutions keeping the constrained satisfied (observability).
11. Replace (elite_size) bad solutions by (elite_size) elite solutions.
12. Again, remove duplicate solutions keeping the constrained satisfied (observability), then determine the teacher.
13. Repeat from step (7) until the maximum number of iterations is reached.
14. Set the best solution $x_{teacher}$ as the final solutions.

The flowchart for the optimal placement algorithm is shown in the following diagram:

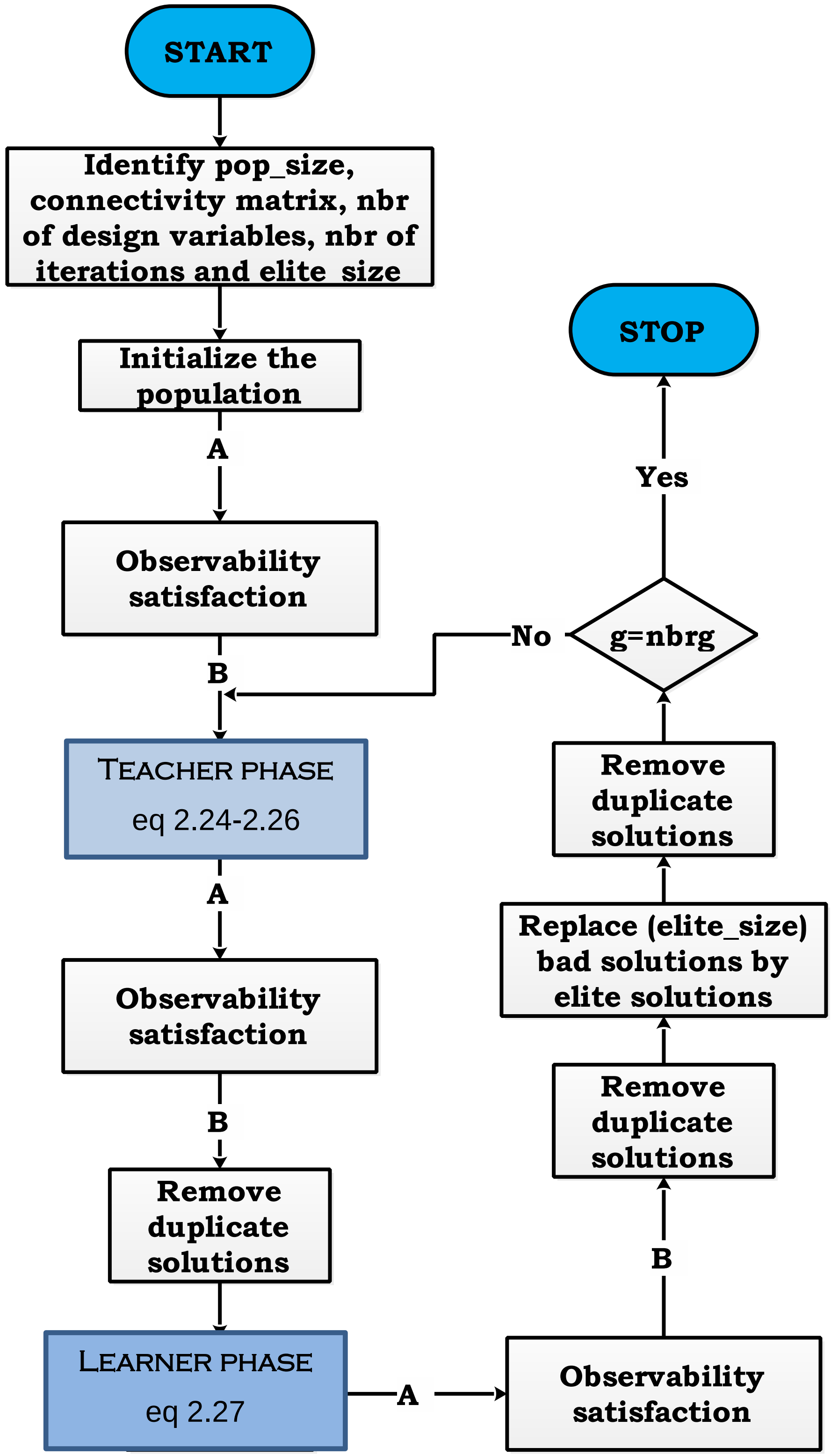


Figure 2-13 TLBO algorithm.

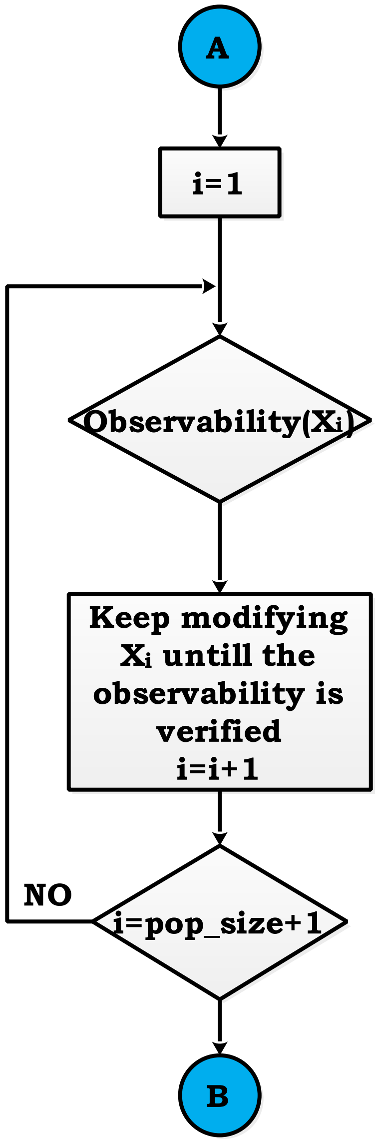


Figure 2-14 Observability analysis

2.11 simulation results

The PMU placement optimization algorithm presented before had been run in MATLAB on the IEEE 14-bus, 30-bus, 57-bus and 118-bus systems. Network data for these systems is in public domain. Detailed system information and simulation results are given in the following sections.

2.11.1 Parameters used

The parameters used in the optimization are: The maximum number of iteration in BTLBO is selected to be 1000 with the population size of 100. In the simulations presented in this work, the best solution of the binary TLBO is concluded after 20 runs of the algorithm. The simulations are carried out on an Intel i5 (2.40 GHz) with 4 GB RAM. It should be mentioned that the corresponding configuration of the required number of PMUs is not necessarily unique. Since heuristic algorithms, such as TLBO, are based on a random search in the search space of the problem, and the result of each execution of these algorithms might be different from another one. Therefore, they must be run several times to ensure that the optimal point of the problem is found. However, from the observability point of view, there is no difference between different configurations with the same number of PMUs, they are difference in redundancy which is not a target on this report, so only one configuration per each case is presented.

2.11.2 Case1: Effect of considering zero injections

Two sets of simulations are carried out on the IEEE bus systems, which are initially assumed to have no flow measurements and no previously existed PMUs. In the first set of simulations, zero injection is simply ignored while in the second set, it is used as existing measurement.

i. IEEE 14-bus system

At first we consider IEEE 14 bus test system (Figure 2-15). This system has got only one zero-injection bus. The output of the BTLBO algorithm is only 3 PMUs. The information of the system and zero injections are given in the Table 2.2.

Table 2.2 System information of IEEE 14-bus system

System	Number of branches	Number of zero injections	Zero injection buses
IEEE 14-bus	20	1	7

Table 2.3 Optimum number and location of PMU without considering zero injection

System	Number of PMUs	Location of PMUs
IEEE 14-bus	4	2,6,8,9

Table 2.4 Optimum number and location of PMU with considering zero injection

System	Number of PMUs	Location of PMUs
IEEE 14-bus	3	2,6,9

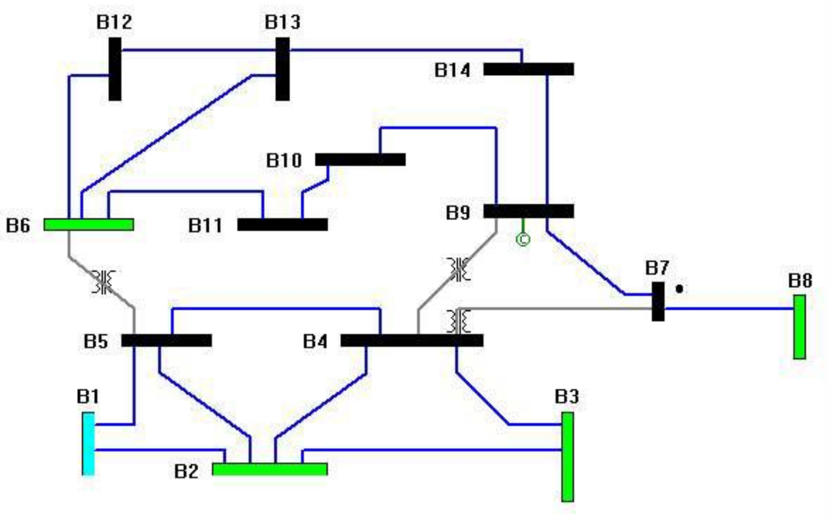


Figure 2-15 IEEE 14-bus system [30].

The global solution is obtained with only a small number of iterations (between 5 and 10) and population size (10). Three PMUs can be deployed to observe the IEEE14 bus system. Here, when ignoring injection, different configuration of PMUs is obtained, whereas, considering injection give only one set (2, 6, and 9). It is observed that the number of PMUs required for system observability reduces by 1, if the system observability is to be maintained after considering zero injections buses.

ii. IEEE 30-bus system

IEEE 30-bus system is shown in Figure 2-16. The Information of the system and zero injections are given in Table 2.5.

Table 2.5 System Information of the IEEE30 bus system.

System	Number of branches	Number of zero injections	Zero injection buses
IEEE 30-bus	41	5	6, 9, 11, 25, 28

Table 2.6 Optimum number and location of PMU without considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 30-bus	10	1, 5, 10, 11, 12, 18, 23, 26, 28, 30

Table 2.7 Optimum number and location of PMU considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 30-bus	7	1, 5, 10, 12, 18, 20, 27

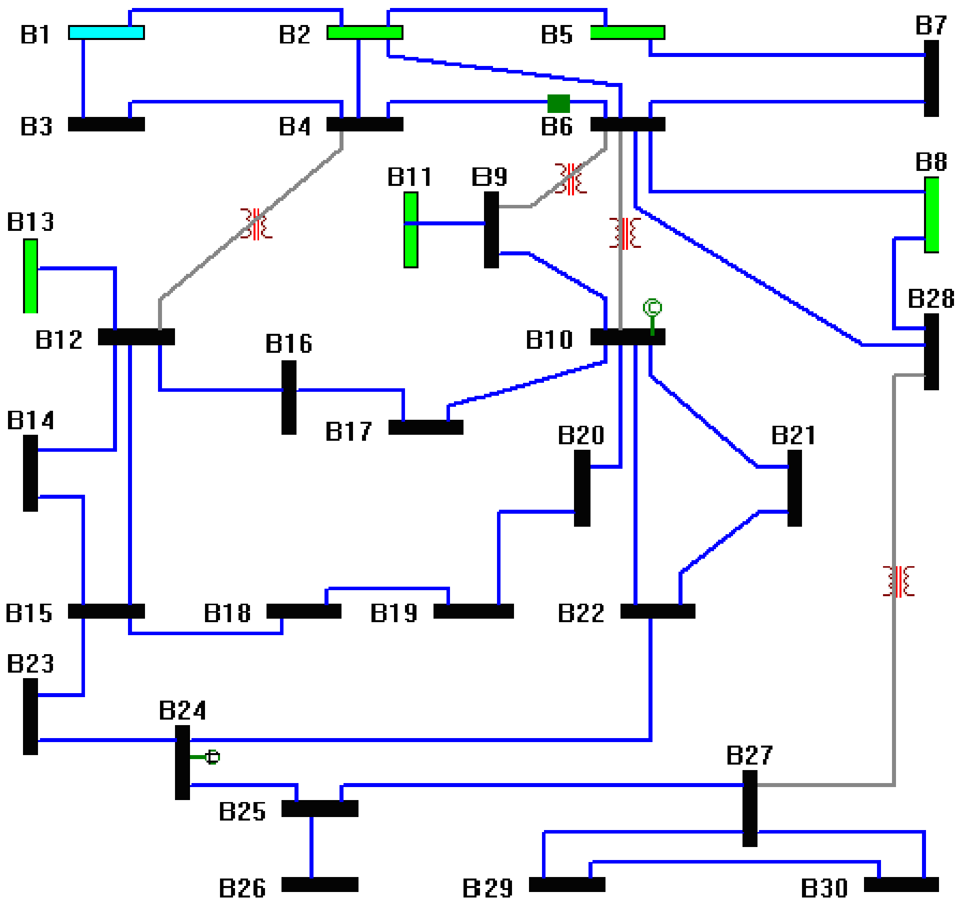


Figure 2-16 IEEE 30-bus system [28].

Table 2.7 brings out results of formulation-OPP under the back-drop of zero injections.

Only 7 PMUs are required for the system to be observable. So having zero injections will reduce the number of required PMUs as can be seen from these results.

iii. IEEE 57-bus system:

IEEE 57-bus system is shown in Figure 2-17. The Information of the system and zero injections are given in Table 2.8.

Table 2.8 System information of IEEE 57-bus system.

System	Number of branches	Number of zero injections	Zero injection buses
IEEE 57-bus	78	15	4, 7, 11, 21, 22, 24, 26, 34, 36, 37 39, 40, 45, 46, 8

Table 2.9 Optimum number and location of PMU without considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 57-bus	17	1, 6, 9, 15, 19, 20, 24, 25, 28, 32, 36, 38, 41, 46, 50, 53, 57

Table 2.10 optimum number and location of PMU with considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 57-bus	11	1, 5, 13, 19, 25, 29, 32, 38, 41, 51, 54

The results obtained for this case support the observations taken for the previous test systems, the number of PMUs reduced from 17 to 10 which is clearly a significant reduced PMU number, only one placement configuration is chosen.

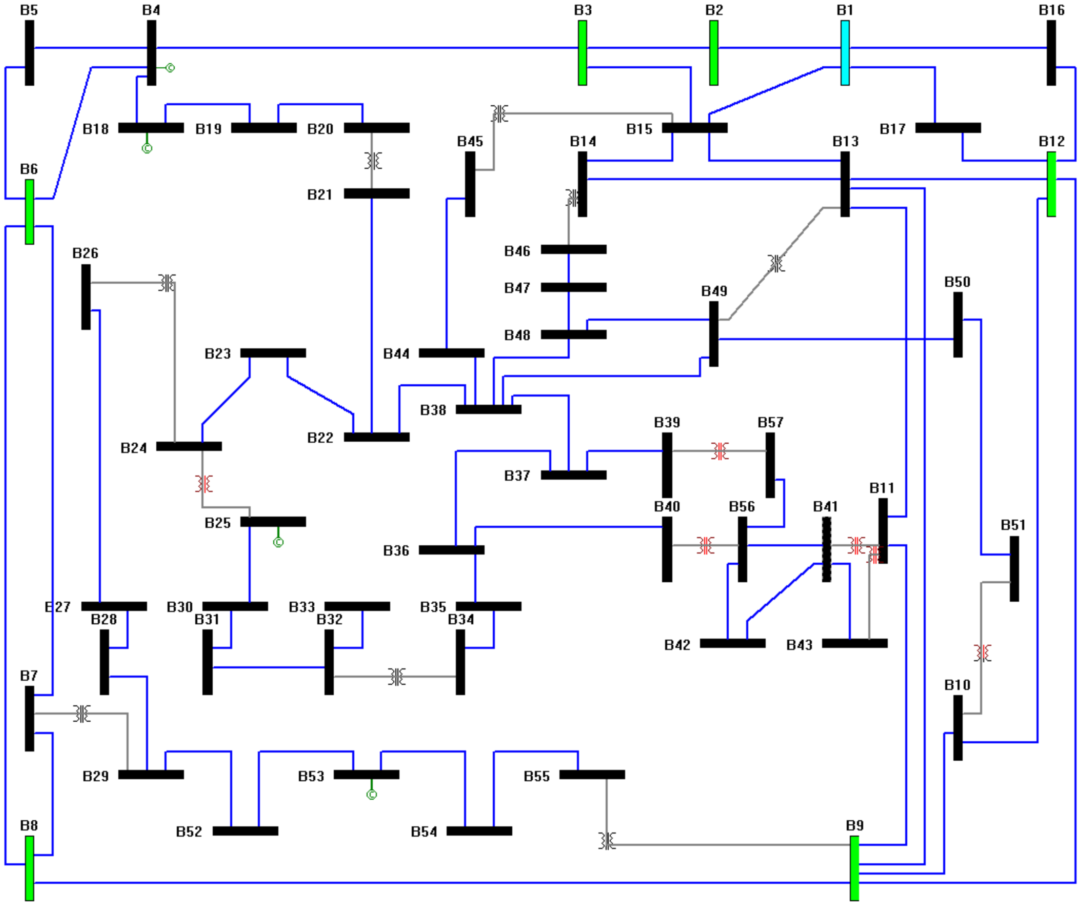


Figure 2-17 IEEE 57-bus system [27] [31].

iv. IEEE 118-bus system (Figure 2-18)

The Information of the system and zero injections are given in Table 2.11.

Table 2.11 System information of IEEE 118-bus system.

System	Number of branches	Number of zero injections	Zero injection buses
IEEE 118-bus	179	10	5, 9, 30, 37, 38, 3, 6 , 68, 71, 81

Results of the IEEE 118 bus system simulated with and without considering the zero injections are tabulated below.

Table 2.12 optimum number and location of PMU without considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 118-bus	32	1, 5, 9, 12, 13, 17, 21, 25, 29, 34, 37, 42, 45, 49, 52, 56, 62, 64, 70, 71, 76, 77, 80, 85, 87, 91, 94, 101, 105, 110, 114, 116

Table 2.13 optimum number and location of PMU with considering zero injection.

System	Number of PMUs	Location of PMUs
IEEE 118-bus	28	3, 8, 11, 12, 17, 21, 27, 31, 32, 34, 39, 42, 45, 49, 53, 56, 62, 72, 75, 77, 80, 85, 87, 90, 94, 102, 105, 110

In this case, the best solution is concluded after 20 runs of the algorithm. For each initial solution, the result is deferent, so the convergence of the algorithm depends strongly on the starting point, the number of deployed PMUs reduced by 4 when considering injection.

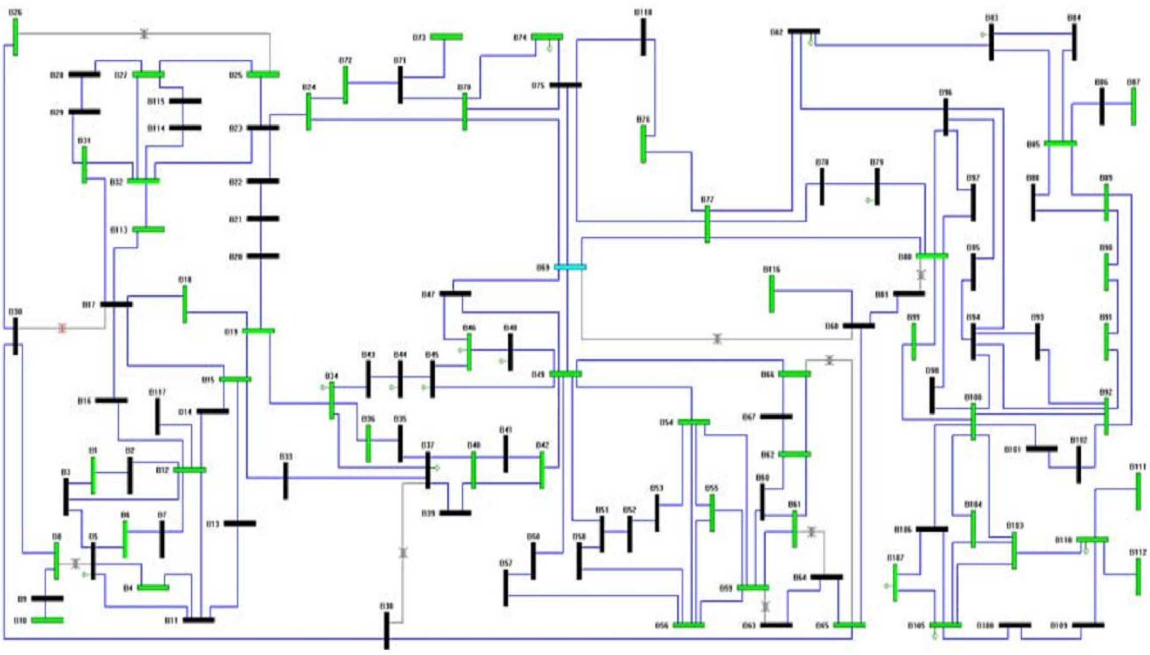


Figure 2-18 IEEE 118-bus system [31].

Case2 Effect of considering conventional measurements

v. flow measurements

In this case, simulations are carried out using IEEE57-bus system. Three sets of flow measurements (P and Q) containing three flow measurements each, are added in the system one at a time. The locations of these flow measurements in the system are given in Table 2.14

Simulation results are shown in Table 2.15. The required number of PMUs is reduced from 11 to 9.

Table 2.14 Locations of flow measurements used for case 2

Meas. set no.	Flow measurements in the et		
1	1–2	14–15	12–17
2	29–52	52–53	53–54
3	41–43	50–51	54–55

Table 2.15 Simulation results considering flow measurements.

System	Flow measurements set	Number of PMUs	Location of PMUs
IEEE57-Bus	None	11	1, 4, 10, 17, 19, 22, 26, 28, 29, 36, 39
	1	10	1, 5, 20, 25, 29, 32, 38, 41, 51, 54
	1 and 2	10	1, 5, 20, 25, 29, 32, 38, 41, 51, 55
	2 and 3	9	1, 5, 20, 25, 29, 32, 38, 41, 51

As tabulated above, The PMUs number is 11 where there are no flow measurements; however this number is reduced by 1 when 3 flow measurements exist, this number is still unchanged when another 3 flow measurements are added to the system, and finally the number is reduced again to 9 PMUs when a total of 9 flow measurements are existed in the system. Hence, as expected, having conventional measurements reduces the number of required PMUs to make the entire system observable.

vi. Already existed PMUs

Here, simulations are carried out using IEEE57-bus system. Three PMUs are added in the system one at a time. The locations of these PMUs in the system are assumed to be in buses 1, 9 and 29

Simulation results are shown in Table 2.16.

Table 2.16 Simulation results considering existed PMUs (case 1).

System	Existed PMU	Number of PMUs	Location of PMUs
IEEE57-Bus	None	1	1, 4, 10, 17, 19, 22 26, 28, 29, 36, 39
	1(bus1)	10	5, 13, 19, 25, 29, 32, 38, 41, 51, 54
	2(bus 1 and 9)	10	5, 13, 19, 28, 30, 33, 38, 41, 51, 53
	3(bus 1, 9 and 29)	9	5,13,20, 25,32, 38, 41,51,53

The required number of PMUs is reduced from 11 to 9. Hence, as expected, having conventional measurements represented by PMUs measurements reduces the number of required PMUs to make the entire system observable. From the second and the third row, one can conclude that already existed PMUs will reduce the required number of PMU if those existed PMUs are installed in suitable locations.

2.12 Comparison of results of BTLBO with different algorithms

For the sake of comparative evaluation, the approach presented above is compared with some of the well-known classical and meta-heuristic algorithms used to solve the problem.

Integer linear programming presented in [28] and [29]has been implemented using the IEEE 14-bus, 30-bus, 57-bus and 118-bus systems and based on the problem formulation presented before (2.6.2). TOMLAB/MINLP and MILP software package was used to solve the Integer Linear/Nonlinear Programming problem.

Table 2.17 shows the obtained results:

Table 2.17 OPP results using integer linear programming.

systems	Ignoring zero injection buses		Considering zero injection buses	
	PMU nb	PMUs location	PMU nb	PMUs location
IEEE14-bus	4	2, 6, 7, 9	3	2, 6, 9
IEEE30-bus	10	2, 6, 9, 10, 12, 15, 18, 25, 27	8	2, 3, 6, 10, 12, 18, 23, 27
IEEE57-bus	17	1, 4, 7, 9, 15, 20, 24, 25, 27, 32, 36, 38, 39, 41, 46, 50, 53	12	1, 5, 9, 14, 15, 20, 25, 28, 32, 50, 53, 56
IEEE118-bus	32	2, 5, 9, 11, 12, 17, 21, 24, 25, 28, 34, 37, 40, 45, 49, 52, 56, 62, 63, 68, 73, 75, 77, 80, 85, 86, 90, 94, 101, 105, 110, 114	28	2, 8, 11, 12, 17, 21, 25, 28, 33, 34, 40, 45, 49, 52, 56, 62, 72, 75, 77, 80, 85, 86, 90, 94, 101, 105, 110, 114

In [31], a topology based genetic algorithm is used, topology-based algorithm is used for observability analysis and a hybrid method of topology transformation and nonlinear constraint is used to form the constraints. The simulation are carried out using the IEEE 14-bus, 30-bus, 57-bus, 118-bus, and the New England 39-bus test systems. Table 2.18 presents the obtained results.

Table 2.18 OPP results using topology based genetic algorithm.

systems	Ignoring zero injection buses		Considering zero injection buses	
	PMU number	PMUs location	PMU number	PMUs location
IEEE 14-bus	4	2, 6, 7, 9	3	2, 6, 9
IEEE 30-bus	10	1, 2, 6, 9, 10, 12, 15, 19, 25, 27	7	1, 2, 10, 12, 15, 20, 27
IEEE 57-bus	18	1, 6, 10, 15, 19, 22, 25, 27, 32, 35, 37, 38, 43, 46, 49, 52, 55, 56	11	1, 5, 13, 19, 25, 29, 32, 38, 41, 51, 54
IEEE118-bus	33	4, 12, 17, 20, 24, 27, 31, 33, 36, 39, 41, 46, 51, 53, 62, 65, 67, 73, 75, 77, 80, 85, 86, 91, 92, 94, 98, 100, 105, 106, 110, 112, 115	29	2, 8, 11, 12, 15, 19, 21, 27, 31, 32, 34, 40, 45, 49, 52, 56, 62, 65, 72, 75, 77, 80, 85, 86, 90, 94, 101, 105, 110

For the study presented in[30], a binary particle swarm optimization (BPSO) based methodology for the optimal placement of PMUs when using a mixed measurement set is used. The optimal PMU placement problem is formulated to minimize the number of PMUs installation subject to full network observability and to maximize the measurement redundancy at the power system buses. Topology-based algorithm is used to ensure full network observability. The efficiency of the method is verified by the simulation results of IEEE14-bus, 30-bus, 57-bus-118 bus systems. The results are shown in the table below:

Table 2.19 OPP results using binary particle swarm optimization algorithm.

systems	Ignoring zero injection buses		Considering zero injection buses	
	PMU nb	PMUs location	PMU nb	PMUs location
IEEE 14-bus	4	2, 6, 7, 9	3	2, 6, 9
IEEE 30-bus	10	2, 4, 6, 9, 10, 12, 15, 18, 25, 27	7	1, 7, 10, 12, 19, 24, 27
IEEE 57-bus	17	1, 4, 7, 9, 15, 20, 24, 25, 27, 32, 36, 38, 39, 41, 46, 50, 53	13	1, 4, 9, 14, 19, 22, 25, 29, 32, 38, 51, 54, 56
IEEE118-bus	32	3, 5, 9, 12, 15, 17, 21, 23, 28, 30, 36, 40, 44, 46, 51, 54, 57, 62, 64, 68, 71, 75, 80, 85, 86, 91, 94, 101, 105, 110, 114	29	2,8,11, 12,15, 19, 21, 27, 31, 32, 34, 40, 45, 49, 52, 56, 62, 65, 72, 75, 77, 80, 85, 86, 90, 94, 101, 105, 110

In order to make a coherent picture of comparison, the results of these three algorithms are tabulated with the BTLBO algorithm in Table 2.20. Since we are interested on the PMUs number and not their locations, Table 22 shows the comparative results of the considered algorithms in the form of the best solution (minimum PMU number); the results are taken in the presence of zero injection buses.

Table 2.20 Comparative results of BTLBO with other algorithms.

Test systems	14-bus	30-bus	57-bus	118-bus
Binary TLBO algorithm	3	7	11	28
Integer programming	3	8	12	28
Topology based genetic algorithm	3	7	11	29
Binary PSO algorithm	3	7	13	29

It is observed from Table 2.20 that the proposed method and all the other methods lead to the same number of PMUs for system observability for the IEEE 14-bus system. For 30-bus system, the performance of the Binary TLBO, GA, and Binary PSO are alike and these algorithms produce better results than integer linear programming. For 57-bus system, the performance of the Binary TLBO and GA are alike, and BTLBO outperforms the Binary PSO algorithm. For 118-bus system, BTLBO and integer programming are alike and BTLBO outperforms GA and binary PSO algorithms.

Each algorithm in the above table fails at least once for example PSO fails twice in the 57bus and in 118 bus, however BTLBO has never failed, it always gets the solution.

To validate the results obtained, the proposed approach are compared with some other algorithms such as Tabu search (Jiangnan et al., 2006), branch and bound [31], nondominated sorting genetic algorithm, graph theoretic procedure, dual search, and Artificial Bee Colony Optimization[32]. Table 2.21 shows the comparison of results. (N/A shows that the result was not available for that case).

Table 2.21 Comparison of results of different algorithms.

Test systems	14-bus	30-bus	57-bus	118-bus
Binary TLBO algorithm	3	7	11	28
Branch and bound algorithm[30]	3	7	12	29
Tabu search[33]	3	N/A	13	N/A
graph theoretic procedure[30]	5	11	19	38
dual search[30]	3	N/A	N/A	29
nondominated sorting GA[34]	3	7	12	29
ABC optimization[35]	3	7	13	29

One can wonder if saving one PUM is important or has some value, yes saving one PMU is so important for the following reasons:

- ✓ PMU costs is so high such that (cost of procurement + installation + commissioning) range between $40,000 and $180,000. [36]

- ✓ In the problem formulation, the economic effect of installing PMU in each bus was ignored to simplify the problem which it can be well reduced by saving one PMU.
- ✓ Even though standard used in the simulation (30, 57, 118) were not so large systems, one PMU was saved in some cases and that sounds promising for large systems.

2.13 Conclusion

In this chapter, the phasor measurement unit PMU is presented as a new technology in advanced power system protection, monitoring and control applications. It is clearly noticed that PMU plays a very important role for the maintenance of power system operation; a brief explanation about PMU mathematical details is pointed out.

A binary teaching learning based optimization method is developed for determining optimal locations for PMUs; various scenarios are considered where the system is first assumed to be observed by PMUs only. Next, the placement problem is considered for a system with existing measurements, some of which may be PMUs.

The above discussion implicitly assumes that all PMUs are free of defects and their failure is not considered as a possibility. In practice, this assumption may not always hold true due to unexpected failures in these devices or gross errors introduced by the noise in the communication system. Therefore, it might be prudent as future challenge to consider the case of PMUs failure as a possible contingency in the formulation and solution of the PMU placement problem.

This chapter also presents the optimization results for the optimal placement of PMUs for making a power system topologically observable. The simulations have some attractive properties where conventional measurements such as injections, flow, and PMUs measurements can also be taken into account if they already exist in the system. The optimization are made on the IEEE 14, 30, 57, and 118 bus test systems, the results indicate that the proposed placement method satisfactorily provides observable system measurements with minimum number of PMUs.

The results also show good improvement in decreasing the number of installed PMUs comparing with earlier applied methods.

Chapter 3: Integration of renewable Energy Resources with HOMER

3.1 Introduction

The lack of electrical energy and the unsustainability of oil sources make the humanity searching for other sources that should be sustainable in order to cover the lack in the grid and to replace the oil sources and therefore decarbonize the electric sources. The integration of renewable energy in grids has many advantages, most of them are:

- Decarbonization: no carbon dioxide is emitted,
- Long term Energy Security: Energy's cost no longer depends on the price of the fossil fuel.
- Expanding energy access: as population grows, the installation of distribution circuits costs more, so fitting the demand will be more difficult therefore building stand-alone systems to serve customers in the rural areas and isolated ones will preserve the grid from losing power if it will be extended.

The objective of this study is to find the number of component of the micro-power system needed for a reliable power (renewable energy+ fossil fuel+ batteries) and cost effective system and that system is supposed to serve a certain load.

The study area is In Salah which located in the south of Algeria, the tool that is used in assessment of wind solar energies is HOMER which is one of the most popular tools in the optimization of integrating renewable energies.

3.2 HOMER

HOMER is a software developed by the U.S. National Renewable Energy Laboratory (NREL) to assist in the design of micropower systems and to facilitate the comparison of power generation technologies across a wide range of applications. HOMER models each component of the hybrid micro-grid , the models are used in the simulation to get the output of each component .Homer finds all feasible solution of such an optimization and rank them according to their total net present cost (TNPC).

A micropower system or a microgrid is a system that generates electricity enough for a load that it serves and it can be connected to the grid or off-grid.

The optimal solution for homer is the one that fits the load fully and satisfies all constraints and has the least total net present cost (TNPC).

3.3 HOMER's physical modeling*

3.3.1 Load:

HOMER models three types of loads. Primary load is electric demand that must be served according to a particular schedule. Deferrable load is electric demand that can be served at any time within a certain time span. Thermal load is demand for heat.

- Primary Load: Primary load is electrical demand that the power system must meet at a specific time. Electrical demand of house appliances is typically modeled as primary load. When a consumer switches on a light, the power system must supply electricity to that light immediately—the load cannot be deferred until later. If electrical demand exceeds supply, there is a shortfall that HOMER records as unmet load.

Since the system must met any change in the primary load, it should provide some surplus amount of power as a reserve for that case and here it comes the importance of operating reserve of the system.

As operating reserve Homer allows the user to specify the operating reserve as a percentage of the load and the renewable output, for e.g.: the operating reserve is 10% of the load, 25% of the wind power and 50% of the solar output; it means that the system must be able to fit the load even if it increases by 10%, the wind power decreases by 25% and the solar power decreases by 50%.

(*) The references of the formulae are written between [], if not the reference is HOMER's Help.

The operating reserve is very important for the *fluctuation* of the load and the *unpredictability* of the renewable resources therefore it decides how much the system is reliable.

- Deferrable Load: Deferrable load is electrical demand that can be met anytime within a defined time interval. Water pumps, ice makers, and battery-charging stations are examples of deferrable loads because the storage inherent to each of those loads allows some flexibility as to when the system can serve them. The ability to defer serving a load is often advantageous for systems comprising intermittent renewable power sources, because it reduces the need for precise control of the timing of power production.
- Thermal Load: HOMER models thermal load in the same way that it models primary electric load, except that the concept of operating reserve does not apply to the thermal load.

3.3.2 Resources:

Resource is anything used to generate electricity: fuel, sun, wind, biomass, water…

The most important ones are: fossil fuel, solar energy and wind energy.

i. Solar Resource:

Solar resource is the energy provided by sun light; to use that resource in the optimization solar data must be available. Solar data needed are Solar Global Horizontal Irradiance (GHI) and clearness index those two are important to calculate the output of PV arrays. Those data should be fully available i.e. if the time step is 1 hour then 8760 data is mandatory, however this is not always the case, sometimes only 12 monthly averaged data is available, in a case like that Homer generates 8760 synthetic data starting from the present data and the altitude of the area using an algorithm developed by Graham and Hollands[37] [38] which is based on stochastic and statistical parameters of solar data.

ii. Wind Resources:

Wind power is the power generated by wind using wind turbines which convert the kinetic energy of the wind into electrical energy; therefore the wind speed is the important parameter of an area to say that this area has a powerful wind. Usually 3 m/s is the threshold wind speed because most of wind turbines cannot generate electricity under that speed.

Wind speed of the whole year must be also given, 8760 for hourly simulation and 525600 for minutely simulation. For incomplete data Homer generates synthetic data from 12 monthly averaged wind speeds and four additional statistical parameters: the Weibull shape factor: a factor related the distribution of the wind over the year.

The autocorrelation factor: expresses how much a wind speed of an hour depends the previous hour and on the same hour on the day before.

The diurnal pattern strength: reflects how strongly the wind speed tends to depend on the time of day.

The anemometer height: the height above ground at which the wind speed data were measured or for which they were estimated.

The hour of peak wind speed: the windiest hour of the day usually it is 15:00.

iii. Fuel:

HOMER provides a library of several predefined fuels. The physical properties of a fuel include its density, lower heating value, carbon content, and sulfur content. The properties of the fuel are the price and the annual consumption limit.

There are other resources such as: Hydro Resource and Biomass Resource but they are not important for the studied area.

3.3.3 Component:

Homer's component is any part of the system that generates converts, delivers or stores energy. In this report PV array, wind turbine, converter, generator and battery bank are the components used.

i. PV Array:

HOMER models the PV array as a device that produces dc electricity in direct proportion to the global solar radiation incident upon it, independent of its temperature and the voltage to which it is exposed. HOMER calculates the power output of the PV array using the equation:

$$P_{PV} = f_{PV} Y_{PV} \frac{I_T}{I_S} \tag{3-1}$$

Where, f_{PV} is the PV derating factor, Y_{PV} the rated capacity of the PVarray (kW), I_T the global solar radiation (beam plus diffuse) incident on the surface of the PV array (kW/m2), and I_S is 1 kW/m2, which is the standard amount of radiation used to rate the capacity of the PV array.

ii. Wind Turbine:

HOMER models a wind turbine as a device that converts the kinetic energy of the wind into ac or dc electricity according to a particular power curve, which is a graph of power output versus wind speed at hub height.

At each time step homer calculate the power output of the wind turbine following steps:

1) It calculates the corresponding wind speed at the turbine's hub height using either the logarithmic law or the power law: $v_2 = v_1 \left(\frac{h_2}{h_1}\right)^{0.14}$, where v_2 is the speed at height h_2 and v_1 is the speed at the reference height i.e. at which wind data are measured.
2) It uses the power curve to get the power associated with the speed previously calculated, Figure 3-1 is the power curve of Bergy XL1 wind turbine, so if $v_2 = 6.5\ m/s$ then the wind power output is around 200 watts

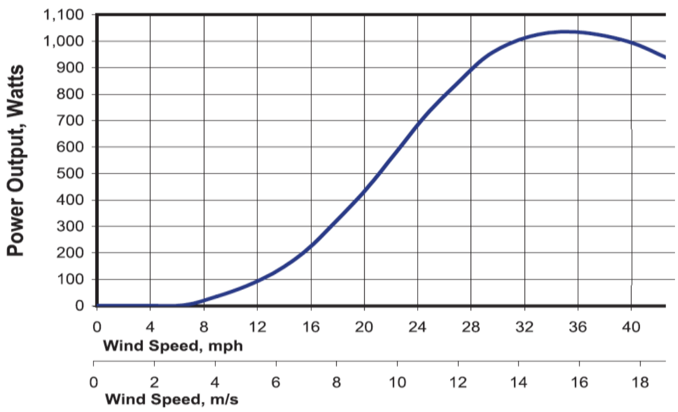


Figure 3-1 BW XL1 Power Curve [42].

3) It multiplies that power output value by the air density ratio, which is the ratio of the actual air density to the standard air density.

iii. Generators:

A generator consumes fuel to produce electricity, and possibly heat. HOMER's generator module is flexible enough to model a wide variety of generators, including internal combustion engine generators, micro turbines، fuel cells, Sterling engines, thermo photovoltaic generators, and thermoelectric generators. HOMER can model a power system comprising as many as three generators, each of which can be ac or dc, and each of which can consume a different fuel.

The principal physical properties of the generator are its maximum and minimum electrical power output, its expected lifetime in operating hours, the type of fuel it consumes, and its fuel curve, which relates the quantity of fuel consumed to the electrical power produced. In HOMER, a generator can use Diesel or gasoline or natural Gas…..or any type of fuel.

HOMER assumes the fuel curve is a straight line with a y-intercept and uses the following equation for the generator's fuel consumption[42]:

$$F = F_0 Y_{gen} + F_1 P_{gen} \qquad (3\text{-}2)$$

Where, F_0 is the fuel curve intercept coefficient, F_1 is the fuel curve slope, Y_{gen} the rated capacity of the generator (kW), and P_{gen} is the actual output of the generator (kW).

iv. Battery Bank:

The battery bank is a collection of one or more individual batteries. HOMER models a single battery as a device capable of storing a certain amount of dc electricity at fixed round-trip energy efficiency, with limits as to how quickly it can be charged or discharged, how deeply it can be discharged without causing damage, and how much energy can cycle through it before it needs replacement.

The key physical properties of the battery are its nominal voltage, capacity curve, lifetime curve, minimum state of charge, and round-trip efficiency.

Homer uses the kinetic battery model to calculate the discharging and charging rates, for the expected lifetime of the battery bank which is given by the following equation[42]:

$$Life_{batt} = min\left(\frac{N_{batt}Q_{lifetime}}{Q_{thrpt}}, Float_{life}\right) \tag{3-3}$$

Where, N_{batt} is the number of batteries in the battery bank, $Q_{lifetime}$ the lifetime throughput of a single battery, Q_{thrpt} the annual throughput (the total amount of energy that cycles through the battery bank in one year), and$Float_{life}$: the float life of the battery (the maximum life regardless of throughput).

v. Converter:

A converter is a device that converts electric power from dc to ac in a process called inversion, and/or from ac to dc in a process called rectification. HOMER can model the two common types of converters: solid-state and rotary.
The converter size, which is a decision variable, refers to the inverter capacity, meaning the maximum amount of ac power that the device can produce by inverting dc power.

3.4 System Dispatch

In addition to modeling the behavior of each individual component, HOMER must simulate how those components work together as a system. That requires hour-by-hour decisions as to which generators should operate and at what power level, whether to charge or discharge the batteries, and whether to buy from or sell to the grid. In this section the logic HOMER used to make such decisions is described briefly.
Each hour of the year, HOMER determines whether the (nondispatchable) renewable power sources by themselves are capable of supplying the electric load, the required operating reserve, and the thermal load. If not, it determines how best to dispatch the dispatchable system components (the generators, battery bank) to serve the loads and operating reserve. This determination of how to dispatch the system components each hour is the most complex part of HOMER's simulation logic. The nondispatchable renewable power sources, although they necessitate complex system modeling, are themselves simple to

model because they require no control logic—they simply produce power in direct response to the renewable resource available. The dispatchable sources are more difficult to model because they must be controlled to match supply and demand properly, and to compensate for the intermittency of the renewable power sources.

The fundamental principle that HOMER follows when dispatching the system is the minimization of cost. HOMER represents the economics of each dispatchable energy source by two values: a fixed cost in dollars per hour, and a marginal cost of energy in dollars per kilowatt-hour. These values represent all costs associated with producing energy with that power source that hour.

So the logic of homer is fitting the load and operating reserve by the renewable power sources if they can otherwise make a decision to run the generator or discharge the batteries (or purchase from the grid if the system is autonomous).

Running the generator or discharging the batteries depends on their economical effects i.e. Homer calculates the marginal cost of each one then it chooses the cheapest one.

Homer uses the following equation to calculate the marginal cost of the battery[42]:

$$marg_{batt}(load) = \left(C_{bw} + C_{b,n}\right) \times \frac{load}{\eta_{inv}} \qquad [\$/hour] \qquad (3\text{-}4)$$

Where:

η_{inv} is the inverter efficiency.

C_{bw} is the wear cost (the cost per kilowatt-hour of cycling energy through the battery bank) which is fixed and calculated by[42]:

$$C_{bw} = \frac{C_{rep,batt}}{N_{batt} Q_{lifethr} \sqrt{\eta_{rt}}} \qquad [\$/Kwh] \qquad (3\text{-}5)$$

$C_{rep,batt}$ is the replacement cost of the battery bank [$].

N_{batt} number of batteries in battery bank.

$Q_{lifethr}$ is the lifetime throughput of a single battery $[Kwh]$.

η_{rt} is the round trip efficiency.

$C_{b,n}$ is the battery energy cost (the average cost of the energy stored in the battery bank) in time step n (at hour n):

$$C_{b,n} = \frac{\sum_{i=1}^{n-1} C_{cc,i}}{\sum_{1}^{n-1} E_{cc,i}} \qquad [\$/Kwh] \tag{3-6}$$

$E_{cc,i}$ the amount of energy that went into the battery bank in time step i [kWh]

$C_{cc,i}$ is the cost of cycle-charging the battery in time step i

$$C_{cc,i} = \begin{cases} 0 & generator\ OFF \\ \frac{P_{gen,batt}}{P_{gen}} \times fuel_{consumption(P_{gen})} \times fuel_{price} & generator\ ON \end{cases} \tag{3-7}$$

[$]

$C_{cc,i}$ is always zero under Load-following dispatch strategy (discussed later) , it is also zero if the battery bank is discharging.

$P_{gen,batt}$ is the extra power generated by the generator which will go to the battery bank.

For the generator marginal cost, Homer calculates the sum of generator's fixed cost energy and generator's marginal costs as[42]:

$$marg_{gen}(load) = C_{gen,ma} \times load + C_{gen,fixed} \qquad [\$/hour] \tag{3-8}$$

Where

$$C_{gen,ma} = F_1 \times fuel_{price} \qquad [\$/Kwh] \tag{3-9}$$

$$C_{gen,fixed} = O\&M_{gen} + \frac{C_{rep,gen}}{L_{gen}} + F_0 Y_{gen} fuel_{price} \qquad [\$/Kwh] \tag{3-10}$$

F_1 is the fuel curve slope $[l/Kwh]$.

F_0 is the fuel curve intercept coefficient $[l/Kwh]$.

$O\&M_{gen}$ is the operating and maintenance of the generator $[\$/hour]$.

$C_{rep,gen}$ is the replacement cost of the generator [$].

L_{gen} The generator lifetime $[hours]$.

Y_{gen} The rated output of the generator$[Kwh]$.

$fuel_{price}$ The effective fuel price (the price of 1 liter – penalties over 1 liter)[$\$/l$].

Whenever the nondispatchable energy sources are unable to meet the load homer make a decision between turning ON the generator and discharging the battery bank by comparing their marginal costs.

HOMER provides two simple strategies to determine the optimal battery-charging strategy and lets the user model them both to see which is better in any particular situation. These dispatch strategies are called load-following and cycle-charging. Under the load-following strategy, a generator produces only enough power to serve the load, and does not charge the battery bank. Under the cycle-charging strategy, whenever a generator operates, it runs at its maximum rated capacity (or as close as possible without incurring excess electricity) and charges the battery bank with the excess.

Because HOMER treats the dispatch strategy as a decision variable, the user can easily simulate both strategies to determine which is optimal in a given situation.

There is also another option in charging the batteries which is the set point, if a set point state of charge is applied, once the system starts to charge the battery bank it will not stop until the battery bank reaches the setpoint state of charge.

3.5 ECONOMIC MODELING [39]

Economics play an integral role both in HOMER's simulation process, wherein it operates the system so as to minimize total net present cost, and in its optimization process, wherein it searches for the system configuration with the lowest total net present cost. Homer calculates the total net present cost by summing the net present costs NPCs of all component.

The net present cost (or life-cycle cost) of a component is the present value of all the costs of installing and operating that component over the project lifetime, minus the present value of all the revenues that it earns over the project lifetime.

3.5.1 NPC of the generator:

$$NPC_{gen} = Cap_{gen} + Rep_{gen} \times K_{gen} + \frac{O\&M_{gen} \times op_h + fuel \times fuel_{price}}{Crf} - S_{gen} \times dis_f \tag{3-11}$$

[42]and HOMER's help

Cap_{gen} is the capital cost of the generator [$].

Rep_{gen} is the replacement cost of the generator [$].

$O\&M_{gen}$ is the operating and maintenance of the generator $[\$/hour]$.

op_h is the number of operating hours of the generator over a year.

$fuel$ is the amount of fuel consumed by the generator over a year $[liters]$ which is founded by the fuel curve.

K_{gen} Single payment present worth (will be defined later).

Crf is the capital recovery factor which is defined as follows:

$$Crf = ri \times \frac{(1+ri)^R}{((1+ri)^R - 1)} \tag{3-12}$$

ri is the real interest rate and R is the lifetime of the project.

dis_f The discount factor is a ratio used to calculate the present value of a cash flow that occurs in any year of the project lifetime. HOMER calculates the discount factor using the following formula: $dis_f = \frac{1}{(1+ri)^R}$

S_{gen} is the salvage cost of the generator which is defined by:

$$S_{gen} = Cap_{gen} \times \frac{(ceil(op_h \times 25) - op_h \times 25)}{L_{gen}} \tag{3-13}$$

$ceil(.)$ is a function that round toward $+\infty$ $(e.g{:}\, ceil(84.02) = 85)$.

L_{gen} is the generator's lifetime in hours if it operates continuously without stopping.

$\frac{(ceil(op_h \times 25) - op_h \times 25)}{L_{gen}}$ Represents how much time it will live in that system or the lifetime under the condition of that system.

3.5.2 NPC of other component:

NPC of component *i* is similar to the above and it is defined as[40]:

$$NPC_i = N_i \times \left(C_{capi} + C_{repi} \times K_i + \frac{C_{o\&mi}}{Crf} - S_i\right) \tag{3-14}$$

Where

N_i is the number of units of component i.

C_{capi} is the capital cost of one unit of *i.*

C_{repi} is the replacement cost of *i.*

K_i is the single payment present worth which is defined as follows:

$$K_i = \sum_{n=1}^{yi} \frac{1}{(1+ri)^{n \times Li}} \tag{3-15}$$

Where, *Li* is the component's lifetime and *yi* is number of replacements of the component *i* during the lifetime of the project which is a simple function of lifetime of the component and the project.

$C_{o\&mi}$ is the operation and maintenance cost of the component.

S_i is the salvage value of *i* which is found by the equation below:

$$S_i = C_{repi} \times \frac{yi \times Li - R}{Li} \tag{3-16}$$

After getting the NPC of each component Homer calculates the total net present cost (TNPC) by:

$$TNPC = \sum_{i=1}^{end} NPC_i \tag{3-17}$$

Homer uses another criterion to know which configuration between all feasible solutions is the most economic one, that criterion is the levelized cost of energy which is calculated using the annualized cost.

The annualized cost is the cost that, if it were to occur equally in every year of the project lifetime:

$$C_{ann} = TNPC \times Crf \tag{3-18}$$

The COE is:

$$COE = \frac{TNPC \times Crf}{\sum_{i=1}^{8760} Load} = \frac{C_{ann}}{\sum_{i=1}^{8760} Load} \quad \left[\frac{\$}{Kwh}\right] \tag{3-19}$$

HOMER performs three principal tasks: simulation, optimization, and sensitivity analysis. In the simulation process, HOMER models the performance of a particular micropower system configuration each hour of the year to determine its technical feasibility and life-cycle cost. In the optimization process, HOMER simulates many different system configurations in search of the one that satisfies the technical constraints at the lowest life-cycle cost. In the sensitivity analysis process, HOMER performs multiple optimizations under a range of input assumptions to gauge the effects of uncertainty or changes in the model inputs. Optimization determines the optimal value of the variables over which the system designer has control such as the mix of components that make up the system and the size or quantity of each. Sensitivity analysis helps assess the effects of uncertainty or changes in the variables over which the designer has no control, such as the average wind speed or the future fuel price.

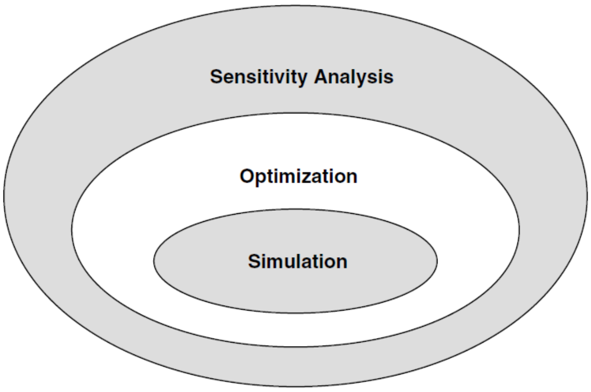


Figure 3-2 Conceptual relationship between simulation, optimization, and sensitivity analysis.

Figure 3-2 illustrates relations between the three process levels in HOMER, sensitivity is a group of optimizations which is a group of simulations.

3.6 The studied Area

The studied area in this project is In Salah which is located in Algeria (27°13.52' North; 2° 27.48' East) and it is at 293m above the sea level. In Salah has an average wind speed of 5.1m/s and an annual daily solar radiation of 5.86 Kwh/m²/day.

3.7 Wind and Solar Potential of the studied area

3.7.1 The wind potential

As mentioned above the annual average wind speed is 5.1 m/s, Figure 1-2 summarize the wind speed profile in In Salah over a typical year[41].

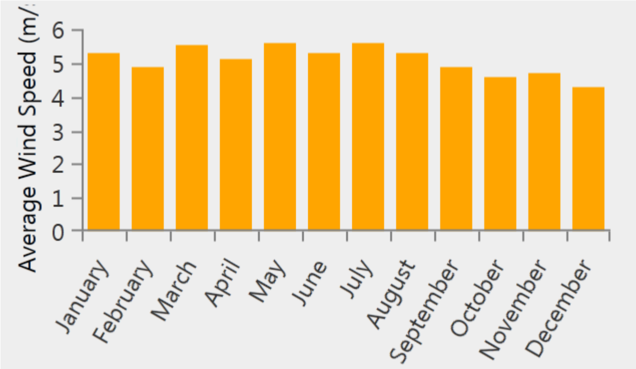


Figure 3-3 The monthly averaged wind speed data.

The area is at 293m above the sea level and those data are measured at 10m above the ground. The distribution of the wind of the year is assumed to follow Weibull Distribution with K=1.85 and the autocorrelation factor is 0.75, the Diurnal pattern strength 0.25 and the hour of peak wind speed is 15 pm.

Variation of wind speed with height follows the power law with power exponent of 0.14

The desert is characterized by the sand and its high temperature. The winds in the desert usually hold sands and this fact makes the power of the wind higher than expected. The real wind speed is higher than the measured one because some of the kinetic energy of the wind transforms to the sand and since the energy is conserved the wind carries the same amount of energy because the meter cube of air now is heavier than before.

3.7.2 The solar potential:

Desert usually has a good solar radiation and that's the case in the desert of Algeria. Figure 3-4 shows the monthly average solar Global Horizontal Irradiance (GHI) and the Clearness index. Solar data are downloaded by HOMER itself.

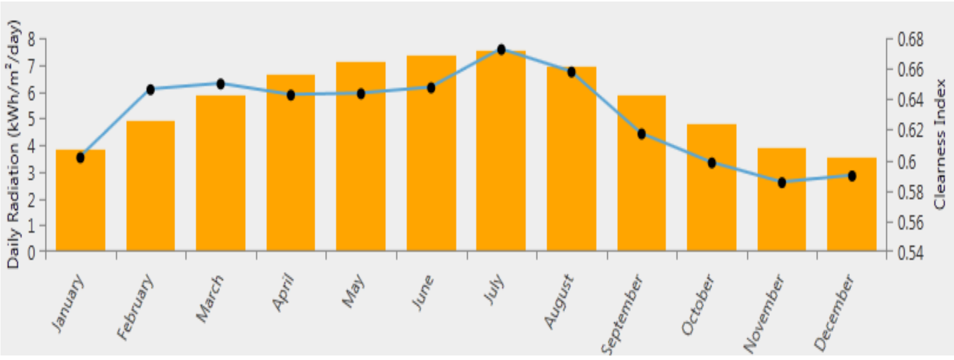


Figure 3-4 the monthly averaged solar Global Horizontal Irradiance

3.8 Problem Specification

3.8.1 The system considered

The system which will be optimized is a standalone PV/wind/battery/diesel hybrid system shown in Figure 3-5

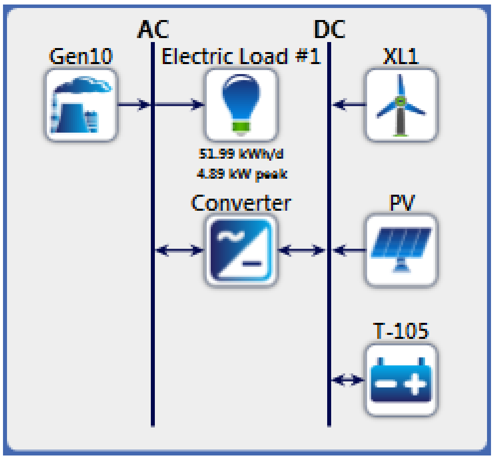


Figure 3-5 The system to be optimized

The wind turbine used here is XL1.

XL1: is manufactured by Bergy Windpower and it has a capacity of 1 Kw and a lifetime of 20 years and a Hub height of 30m and its power curve is shown in Figure 3-6

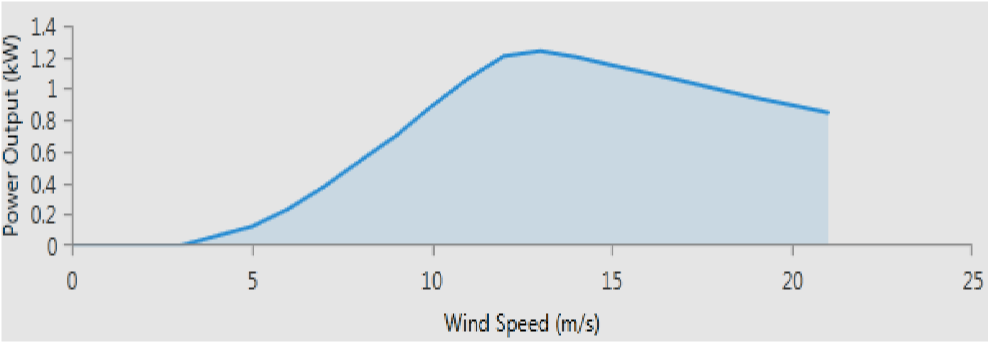


Figure 3-6 XL1 wind turbine power curve

Gen10: is 10Kw gasoline generator which has linear consumption of fuel shown in Figure 3-7

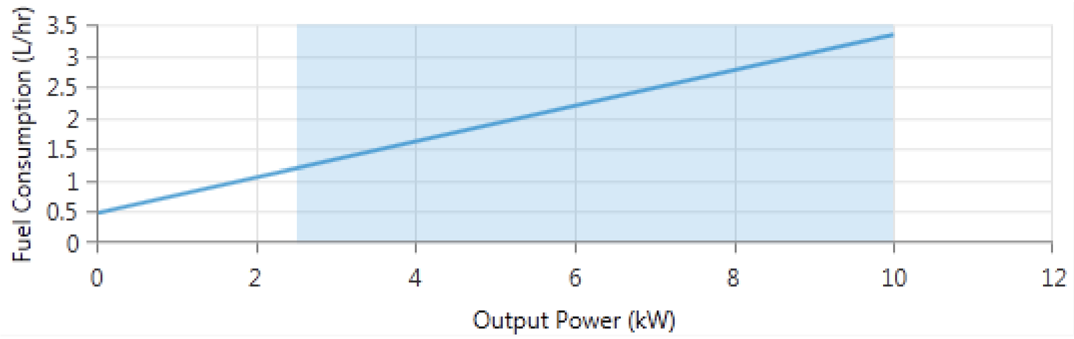


Figure 3-7 G10 fuel consumption.

T-105: is manufactured by Trojan Battery Company and it is a 6V battery with 225 Ah nominal capacity, 865Kwh lifetime throughput, the minimum state of charge is 30% and the Round Trip Efficiency is 85%.

PV: Generic flat plate PV can generate up to 1Kw and it has a lifetime of 25 years.

Converter: has a lifetime of 15 years and an inverting efficiency of 90% and rectifying efficiency of 90%.

Table 3.1 summarizes the search space of each component with the capital cost, the replacement cost and the maintenance and operation cost (O&M).

Table 3.1 Cost and the search space of the system considered.

Component name	Capacity (Kw)	Capital cost ($)	Replacement cost $)	O&M co t ($/year)	Search space
XL1	1	4500	4500	20	01,2,…,5
Gen10	10	2,750	2,750	0.3 [$/hour]	0, 10
T-105	1.35 Kwh	220	220	4	0,19,…34
Converter	1	750	750	0	0,1,…,6
PV	1	3,000	3,000	10	0,2,…7

In order to test the robustance of the system, two sensitivity variables have been considered: the fuel price, the wind speed as shown in Table 3.2.

Table 3.2 Sensitivity Inputs.

Sensitivity variable (uncertainty)	Values
Diesel Price ($)	0.15 0.2 0.25
Annual wind speed average (m/s)	3 4 5.1

3.9 Project setup

The annual nominal interest rate (nri) of this project is 8% with an expected inflation rate f of 2% which gives a real interest rate of 5.88% knowing that:

$$\boldsymbol{ri} = \frac{\boldsymbol{nri} - \boldsymbol{f}}{\boldsymbol{1} + \boldsymbol{f}} \tag{3-20}$$

The simulation time step is hour (8760 hour in the year).

For the dispatch strategy the Load-following and Cycle-charging dispatch strategies have been considered both to see which one is better.

For the constraints i.e. the operating reserve:

The system must serve the load even if:

- The load suddenly increased by 10%.
- The wind power output suddenly decreased by 30% (sensitivity variables).
- The solar power output suddenly decreased by 25%.

A feasible solution must satisfy all of the above constraints at the same time

3.9.1 <u>The load profile:</u>

Profiling the load is the most important part in sizing micropower systems because sizing the component depends on not only how much power is needed but also how it is consumed i.e. the pattern of the consuming power .

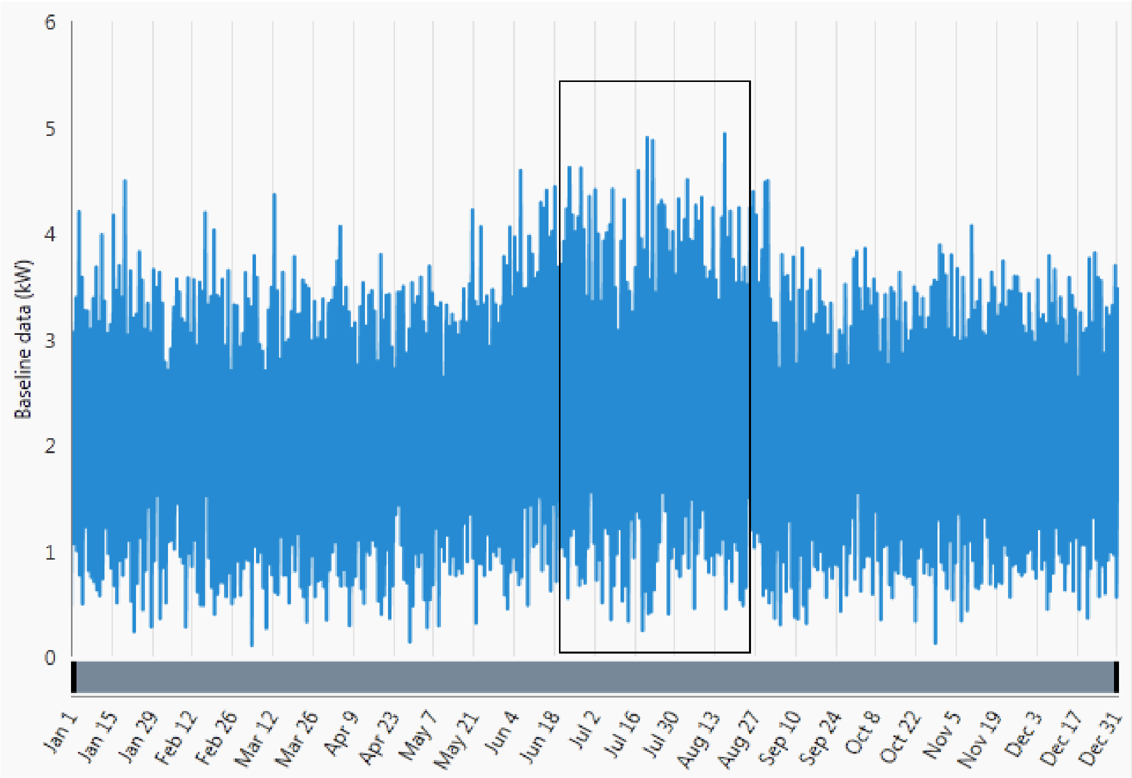
For that reason, special load profile has been created knowing the way that power is consumed in the vicinity of the studied area. Electricity in the desert where the temperature is high in the summer is consumed with a larger amount than other seasons.

Usually the hottest month in the year is July and the hottest hour in a day of summer is 14:00, therefore the peak load in the year happens in July month and daily peak load in summer occurs at 14:00.

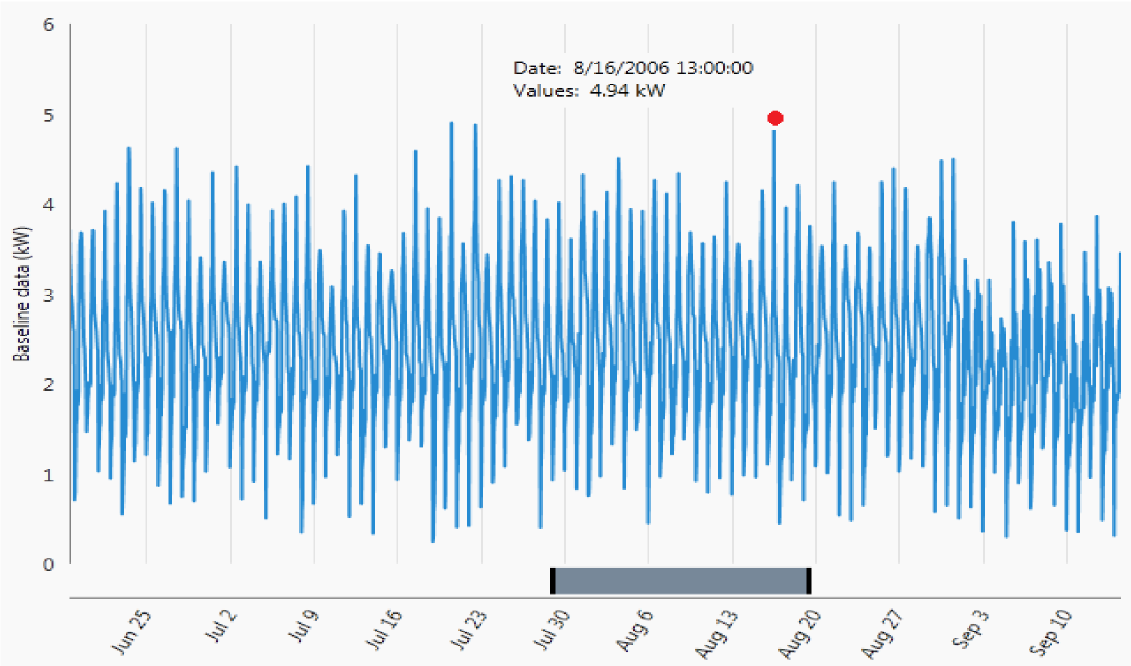
For the other seasons the daily peak load occurs at 18:00 when all the family members are at home therefore electricity is consumed more at that hour.

The annual average load is 51.95 Kwh/day which is sufficient to supply few houses,

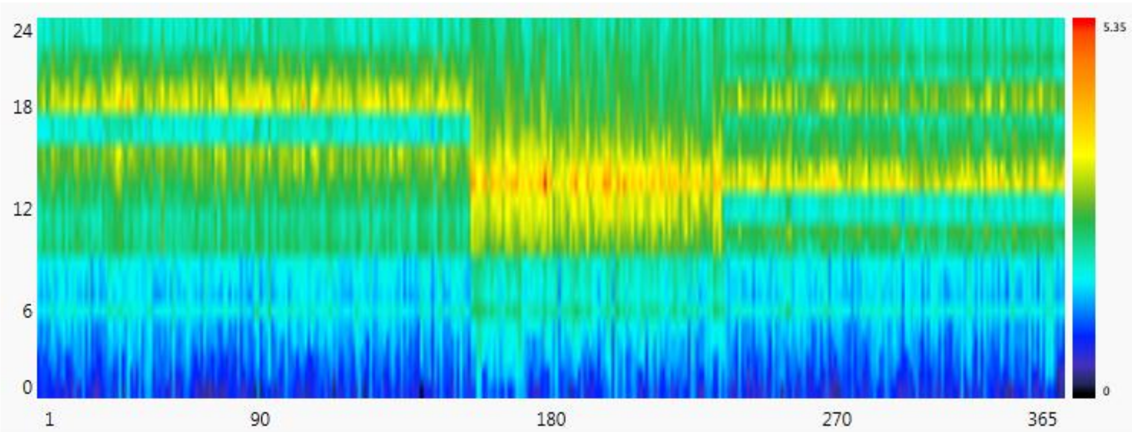
The hourly, seasonal and yearly load profile of the typical rural area is shown in Figure 3-8.



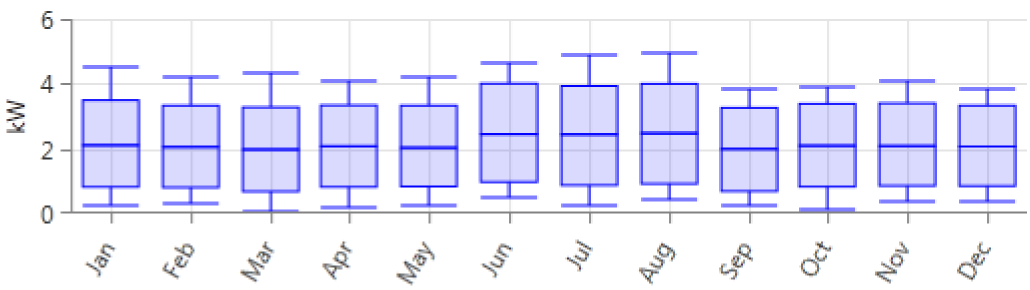
(a)



(b)



(c)



(d)

Figure 3-8 Load profile

The annual load profile, (b) zoom load profile around the peak load, (c) the Dmap of the load, (d) the seasonal load profile

3.10 Optimization and Sensitivity Results

3.10.1 Optimization

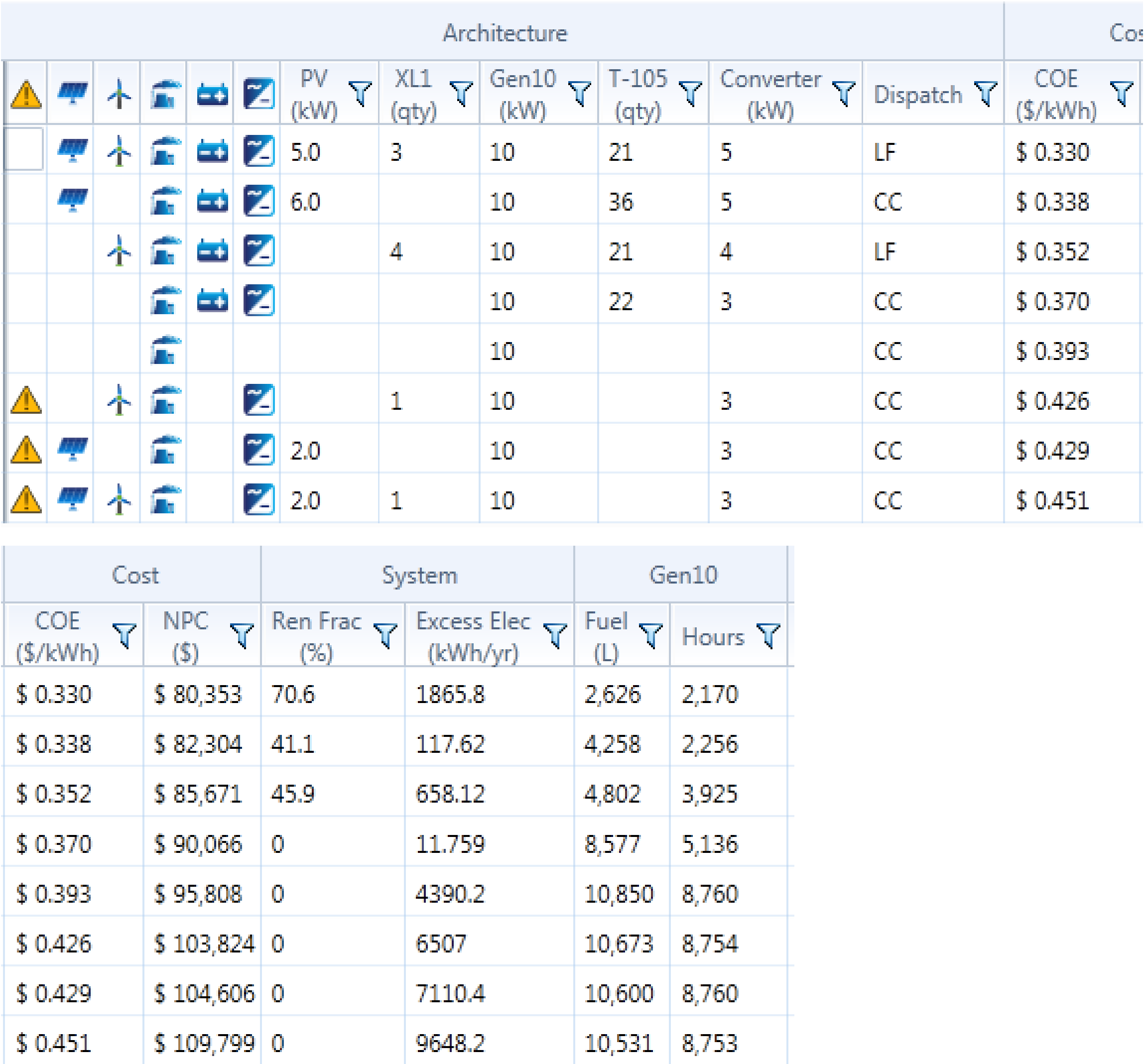
Homer lists the optimization results ranked according to their COEs, if two systems appears to have the same COE Homer decides who the best is by looking to the annualized NPC. So the first system 5Kw PV/ 3Kw XL1/10Kw Gen10/21 T-105/4Kw Converter is the optimal solution that satisfies the constraints with the least COE and its renewable factor is 70.6 %.

The results are categorized according to their configuration i.e.:

- The first row is PV/Wind/Gen/Battery.
- The Second is PV/Gen/Battery.
- The third is Wind/Gen/Battery.
- The fourth is Gen/Battery.
- The fifth is Gen.
- The sixth is Wind/Gen.
- The seventh is PV/Gen.
- The eighth is PV/Wind/Gen.

Those different configurations are the feasible solutions and Wind/PV/Battery is missing here, therefore it is not a feasible solution and hence the area cannot be supplied by 100% renewable sources or at least supplying the area just by renewable energies will cost so much.

One can conclude from Figure 3-9 that the optimal system configuration is: PV/Wind/Gen/Battery with load-following dispatch strategy which means that the area has powerful renewable energies since charging batteries can be done only by solar and wind output. That result proves that In Salah has considerable Wind and Solar potential



Architecture							Cost
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch		COE ($/kWh)
5.0	3	10	21	5	LF		$ 0.330
6.0		10	36	5	CC		$ 0.338
	4	10	21	4	LF		$ 0.352
		10	22	3	CC		$ 0.370
		10			CC		$ 0.393
	1	10		3	CC		$ 0.426
2.0		10		3	CC		$ 0.429
2.0	1	10		3	CC		$ 0.451

Cost		System		Gen10	
COE ($/kWh)	NPC ($)	Ren Frac (%)	Excess Elec (kWh/yr)	Fuel (L)	Hours
$ 0.330	$ 80,353	70.6	1865.8	2,626	2,170
$ 0.338	$ 82,304	41.1	117.62	4,258	2,256
$ 0.352	$ 85,671	45.9	658.12	4,802	3,925
$ 0.370	$ 90,066	0	11.759	8,577	5,136
$ 0.393	$ 95,808	0	4390.2	10,850	8,760
$ 0.426	$ 103,824	0	6507	10,673	8,754
$ 0.429	$ 104,606	0	7110.4	10,600	8,760
$ 0.451	$ 109,799	0	9648.2	10,531	8,753

Figure 3-9 Optimization Results

The last three configuration have PV arrays and XL1 and none batteries, and that can cause stability problem as mentioned by Homer , that's why they have yellow signs.

3.10.2 Sensitivity Analysis:

Figure 3-9 shows the sensitivity result for the change in fuel price and wind speed variable, as it can be noticed the region of PV /Gen/Battery is much bigger than that of PV/XL1 /Gen/Battery and that can be returned to many factors:

-the PV panel and wind turbine have almost the same rated power but with different NPCs

- The operating reserve of wind speed is 30%.

- The studied area has a solar power greater than wind power.
- The stochastic parameters of the two time series i.e. the wind speed profile and global horizontal solar irradiation.

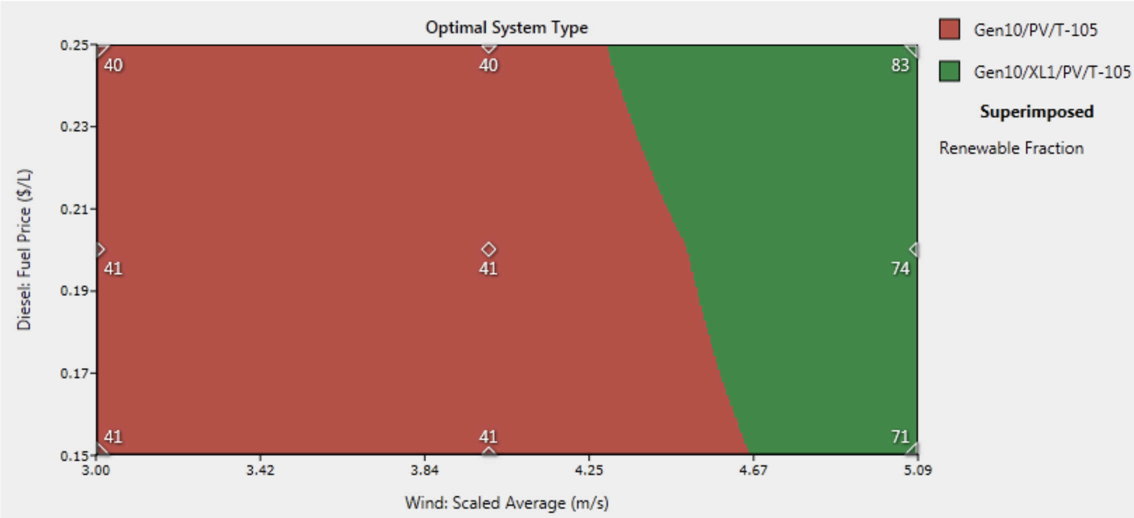


Figure 3-10 The sensitivity results (wind speed vs. fuel price).

The sensitivity results show that the increasing in fuel price makes the PV/XL1/Gen/Battery better than PV/Gen/Battery system.

Figure 3-11 shows a comparison between grid extension cost and the TNPC of the standalone system first ranked in Homer results shown in Figure 1-10.

As it can be seen the stand alone is cheaper than the grid extension starting from a distance of 1.2 km therefore generating electricity from renewable energies is the appropriate solution in rural areas in In Salah.

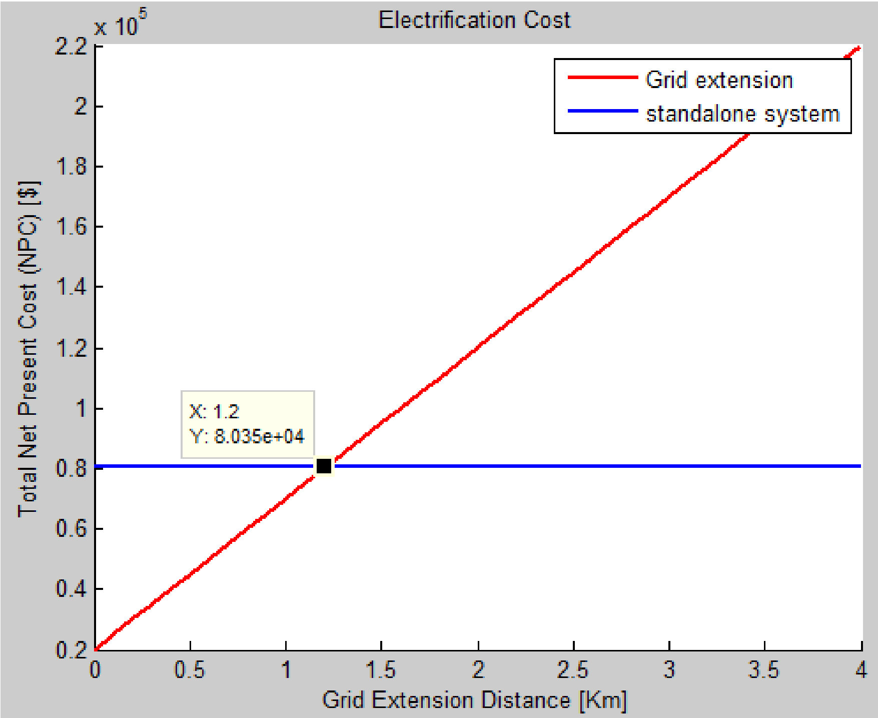


Figure 3-11 Comparison between stand alone and grid connection alternatives

3.11 Conclusion

Renewable Energies are pure and sustainable sources of electricity; furthermore producing electricity by renewable energies is the most economical way but that all depends on the ability of the area i.e. the solar and wind potentials. The variety of renewable energies also is an advantage, the coastal areas usually have a weak solar and wind energy potential but they have wave energy potential , other areas don't have all of that but they have rivers which can be useful.

The integration of renewable energies is an optimization problem; Homer is an option to solve. Homer gives the user all feasible solutions ranked economically and let him decide which one is the most appropriate for his study because there are other constraints which can make a solution more appropriate like excess energy which is can be in huge amount in the optimal solution. Homer provides some constraints to get not only an economic configuration but an economic configuration that provides a reliable electric power and that is through operating reserve. Homer has also sensitivity analysis part to test the robustance of the systems.

Homer is a powerful tool in its field but it has some disadvantages like: the probability to be tricked by the local minimum for the beginners, the time of simulation is huge for wide ranges of the decision variables. Homer tries all possible combination from the ranges of the decision variables and that what makes the simulation heavy, for that reason a metaheuristic algorithm is an option to find the global minimum with a less computations.

In this study, the optimization of a hybrid standalone Wind/Solar/Diesel based energy system has been considered for the site of In Salah. The optimization task has been carried using HOMER which successfully determined the best technical and economic system to adopt for the site. The work has successfully demonstrated that the region possesses a large potential of both solar and wind energies. In the end, it has been also found that hybrid renewable energy system present a better alternative than those connected to grid especially in remote areas.

Chapter 4: Integration of renewable Energy Resources using TLBO

4.1 Introduction

At present, many studies focus on the optimization of standalone electrification systems without considering micro-grid design. In this sense, software tools are broadly used for simulating, optimizing, and sizing of such systems. The utilized software tools have been named as: HOMER, HYBRID2, HYBRIDS, HOGA, PVSYST, SOMES, RAPSIM, SOLSIM, INSEL, PV-DESIGN PRO, RSHAP, and ORIENTE. Nevertheless, HOMER[42] (hybrid optimization model for electric renewables) is so far the most common tool for cost, sensitivity analysis, and validation tests of hybrid stand-alone systems. However, these softwares have their own disadvantages, such as black box utilization, i.e. the user cannot change the power management algorithm even though Homer provides a lot of option to the user[43]. The computational optimization methods using bio-inspired technologies have also been significantly developed in recent years. They can effectively increase the efficiency of hybrid systems by finding the best configuration to optimize the technical and economic criteria.

Genetic algorithm (GA) is an efficient method to optimize the sizing of hybrid systems[44], especially in complex systems, where a large number of parameters have to be considered. It provides a variety of hybrid systems with different sizes of components to satisfy the load demand in a given location and evaluates them according to the defined fitness function, the GA is not easy to code, especially for optimization of HMGS.

Particle swarm optimization (PSO) is another method that can be pointed out as being a simple concept[45], with easy coding implementation, robustness to control parameters, and computational efficiency by generating high-quality solutions with shorter calculation time and stable convergence characteristics[46][47]. PSO performance is comparable to genetic algorithm, but it is faster and less complicated; it has also successfully been applied to a wide variety of problems. It is simple to implement and is an efficient global optimizer for continuous variable problems [20]. PSO has become one of the favorite optimization methods as it presents high speed of convergence for single-objective optimization[48].

However the works done in this field seem to be promising , but they still below Homer because they provide a simple model for the components specially the battery. An algorithm called “Teaching-learning-based optimization” appears recently to the existence and it is a new star in the field of optimization. TLBO for Micropower system optimization have been developed in this chapter with modeling of the components similar to Homer modeling in order to see the differences between Homer and the metaheuristic method in the field of sizing the micropower system.

4.2 The load profile

The load was synthetically generated to be close to the load in the desert, as described in the previous chapter. As it is known the desert is very hot in summer therefore from 12:00 to 17:00 is the time in which the electricity is consumed in considerable amounts, the peak load time is taken 14:00. In the other season the consuming of the electrical energy is less than in summer, the peak load time is 18:00 because in that time all family members are at home. The peak load over the years occurs in 16th of august, exactly at 13:00. Figure 3-8 shows the detailed load profile.

4.3 The Solar/Wind potential

In HOMER, a 12 data of the average monthly wind speed/GHI is enough to run the optimization process but in TLBO an 8760 time series data is needed, and for a fair comparison the 8760 data generated by Homer is used for that purpose.

Figure 4-1 shows the 8760 hourly wind speed and GHI (Figure 4-2).

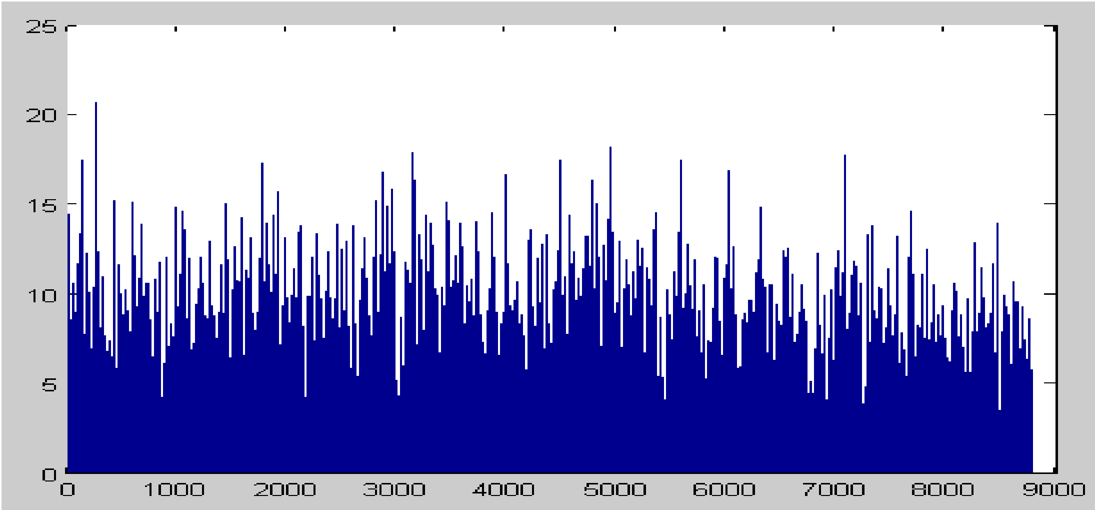


Figure 4-1 Wind speed

Wind speed time series (mean=5.09, variance=8.35, max=20.7, min=0).

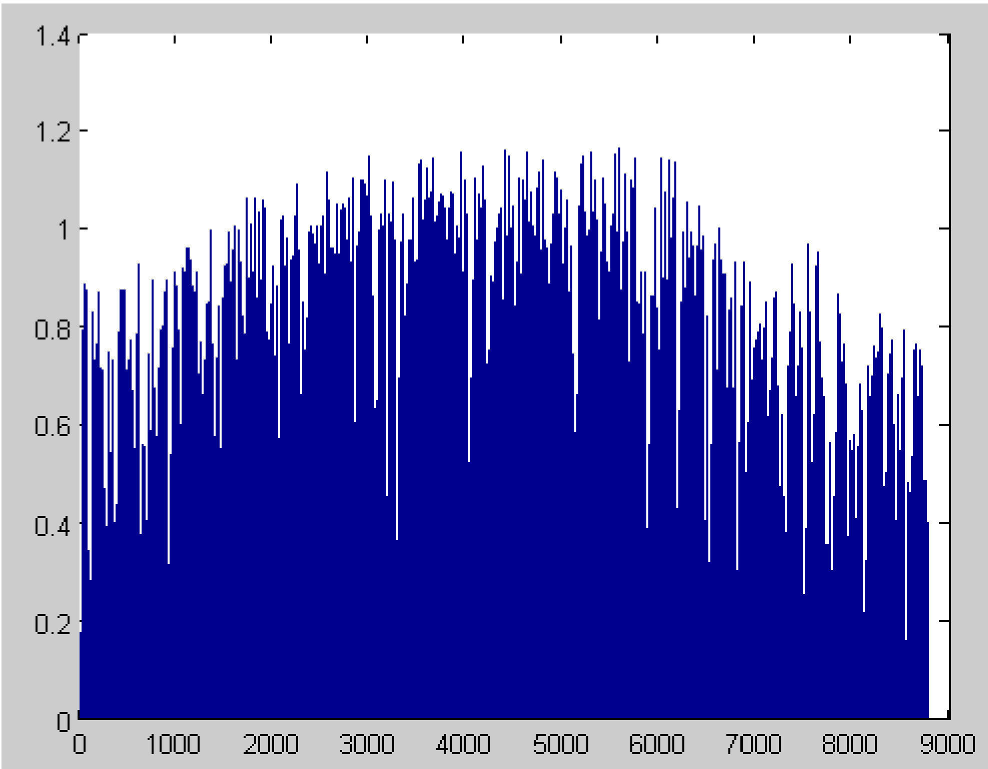


Figure 4-2 Solar radiation

Global Horizontal Irradiation time series (mean=5.89, variance= 0.11, max=1.17, min=0).

4.4 Modeling the components

As mentioned above the power output of a single unit of wind turbine (model: BWXL) and solar panel were imported from Homer results, therefore the model is not needed for those two.

4.4.1 Battery model

Modeling the battery bank includes: the energy content (which is directly related to the state of charge), the maximum charge power , the maximum discharge power, energy in, energy out , annual throughput and the expected life, those will be explained shortly.

a. The energy content [52] [49][50]

The initial battery state of charge is assumed to be 100% and during the charging process is expressed by:

$$en_{content}(t) = en_{content}(t-1) + \eta b_{ch} \times \left(PV_{out} + Pwind_{out} + \frac{Gen_{out} - load}{\eta_{inv}} \right) \tag{4-1}$$

$en_{content}(t)$ is the energy content at the current hour, $en_{content}(t-1)$ is the energy content at the previous hour, PV_{out} is the output power of the PV arrays, $Pwind_{out}$ is the output power of the wind turbines, Gen_{out} is the output power of the diesel generator, $load$ is the load at the current hour t, η_{inv} is the inverter efficiency, ηb_{ch} is the battery charging efficiency which is the square root of the round trip efficiency: $\eta b_{ch} = \sqrt{\eta_{rntr}}$

The energy content for the discharging process:

$$en_{content}(t) = en_{content}(t-1) - \frac{1}{\eta b_{dis}} \left(\frac{load - \mathrm{Gen}_{out}}{\eta_{inv}} - PV_{out} - Pwind_{out} \right) \tag{4-2}$$

ηb_{dis} is the discharging efficiency : $\eta b_{dis} = \eta b_{ch} = \sqrt{\eta_{rntr}}$.

b. The maximum charge power [51]

As described in Homer's Help, HOMER imposes three separate limitations on the battery bank's maximum charge power. The first limitation comes from the kinetic battery model. As described in the article on the kinetic battery model[51], the maximum amount of power that can be absorbed by the two-tank system is given by the following equation:

$$P_{batt,max1} = \frac{kQ_l e^{-k\Delta t} + Qkc(1 - e^{-k\Delta t})}{1 - e^{-k\Delta t} + c(k\Delta t - 1 + e^{-k\Delta t})} \tag{4-3}$$

where

Q_l is the available energy [kWh] in the battery at the beginning of the time step,

Q is the total amount of energy energy [kWh] in the battery at the beginning of the time step,

c is the battery capacity ratio [unitless],

k is the battery rate constant [h^{-1}], and

Δt is the length of the time step [h].

$$P_{batt,max2} = \frac{(1 - e^{-\alpha\Delta t})(Q_{max} - Q)}{\Delta t} \tag{4-4}$$

The third limitation relates to the battery's maximum charge current. The maximum battery bank charge power corresponding to this maximum charge current is given by the following equation:

$$P_{batt,max3} = \frac{N_{batt} I_{max} V_{nom}}{1000} \tag{4-5}$$

Where N_{batt} is the number of batteries in the battery bank.

I_{max} is the battery's maximum charge current [A]

V_{nom} is the battery's nominal voltage [V].

HOMER sets the maximum battery charge power equal to the least of these three values, assuming each applies after charging losses, hence:

$$P_{batt,max} = \frac{MIN(P_{batt,max1}, P_{batt,max2}, P_{batt,max3})}{\eta b_{ch}} \tag{4-6}$$

c. <u>The maximum discharge power</u>

The maximum amount of power that the battery bank can discharge over a specific length of time is given by the following equation:

$$P_{batt,max1} = \frac{-kcQ_{max} + kQ_l e^{-k\Delta t} + Qkc(1 - e^{-k\Delta t})}{1 - e^{-k\Delta t} + c(k\Delta t - 1 + e^{-k\Delta t})} \qquad (4\text{-}7)$$

HOMER assumes that the discharging losses occur after the energy leaves the two-tank system; hence the battery bank's maximum discharge power is given by the following equation:

$$P_{batt,maxdis} = P_{batt,max} \eta b_{dis} \qquad (4\text{-}8)$$

Energy in, energy out: is the energy that goes inside the battery bank or the energy that goes out of the battery and it simply the difference between the energy content of the current hour and the previous one.

Annual throughput: is the amount of energy that cycles through the battery bank in one year. Throughput is defined as the change in energy level of the battery bank, measured after charging losses and before discharging losses.

d. The expected life

As described in the previous chapter the expected lifetime of the battery:

$$Life_{batt} = min\left(\frac{N_{batt} Q_{lifetime}}{Q_{thrpt}}, Float_{life}\right) \qquad (4\text{-}9)$$

In HOMER, two independent factors may limit the lifetime of the battery bank: the lifetime throughput and the battery float life. In other words, batteries can die either from use or from old age.

The generator model is the same of homer described earlier.

4.4.2 Converter/inverter

The converter/inverter is a modeled as a linear device whose output is a fraction of the input:

$$conv/inv_{out} = \eta_{inv} \times conv/inv_{in} \qquad (4\text{-}10)$$

η_{inv} is the efficiency of invesion/rectification which is taken as 90%.

4.5 The feasibility (reliability) of a system

For the feasibility Homer simulate each system chronologically and see if the load is met always, another way to test the feasibility is to calculate the reliability at each time step. The reliability is measured by the loss of power supply (LPS) which is defined by:[52]

$$LPS(t) = load(t) \times \Delta t - \left((PV_{out} + Pwind_{out} + Gen_{out})\Delta t + en(t-1) - en(t)\right) \tag{4-11}$$

$en(t-1) - en(t)$ is the difference between the energy stored in the battery in the current and previous hour.

$(PV_{out} + Pwind_{out} + Gen_{out})\Delta t$ the produced energy from hour t-1 to hour t.

The above difference cannot be negative, so when it is negative it will be replaced by 0.

If LPS=0, it means that the load is fitted, otherwise it is not.

The loss of power supply probability (LPSP) is defined as: [53][54]

$$LPSP = \frac{\sum_{t=1}^{8760} LPS(t)}{\sum_{t=1}^{8760} load(t)} \tag{4-12}$$

LPSP=0 means that the load is always satisfied, LPSP=1 the load is never be satisfied.

4.6 Problem Specification [55]

4.6.1 The system considered

The same hybrid system is considered as earlier (Figure 4-3), with the same parameters mentioned earlier.

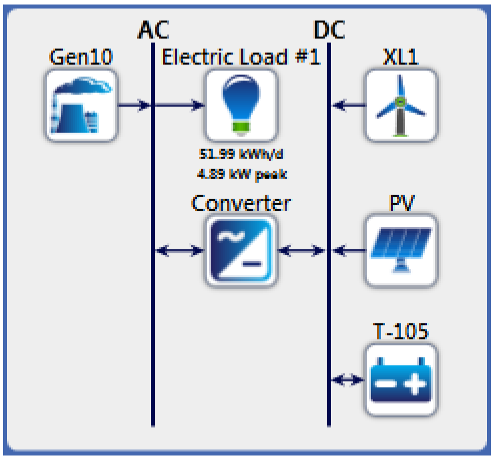


Figure 4-3 The system to be optimized.

4.7 Project setup

The annual nominal interest rate (nri) of this project is 8% with an expected inflation rate f of 2% which gives a real interest rate of 5.88%

For the dispatch strategy the Load-following and Cycle-charging dispatch strategies have been considered both to see which one is better. For simplicity the operating reserve is not considered.

4.8 The power management strategies

The power management is split into two parts like Homer: Cycle-Charging (CC) and Load-Following (LF).

4.8.1 The Cycle-Charging strategy

The cycle-charging (CC) dispatch strategy is implemented following the steps below:

-In each time step, the mode is checked, mode 1 is the mode of charging the battery where the battery should be charged until $SOC \geq 80\%$ then the system is switched to mode0 where the battery can be discharged if it is needed or charged if there is an excess energy.

- The load is always served by the renewable components if they can otherwise the battery bank energy or the generator power will be used depending on the lowest marginal cost (explained in section 3.4) of the current load for the generator and the current load inverted for the battery bank.

-If the renewable components and the batteries cannot serve the load, the generator goes ON without checking the marginal cost and in that case the mode will be switched to mode 1.

-At the end of the time step, the system reliability is calculated (LPS) to be summed with other LPSs after computing the last LPS ($LPS(8760)$).

It should be noticed that the generator cannot generate a power less than 25% of its rated power.

The flowchart was divided into two parts (1 and 2), because it is too large.

Figure 4-4, Figure 4-5 and Figure 4-6 show the details.

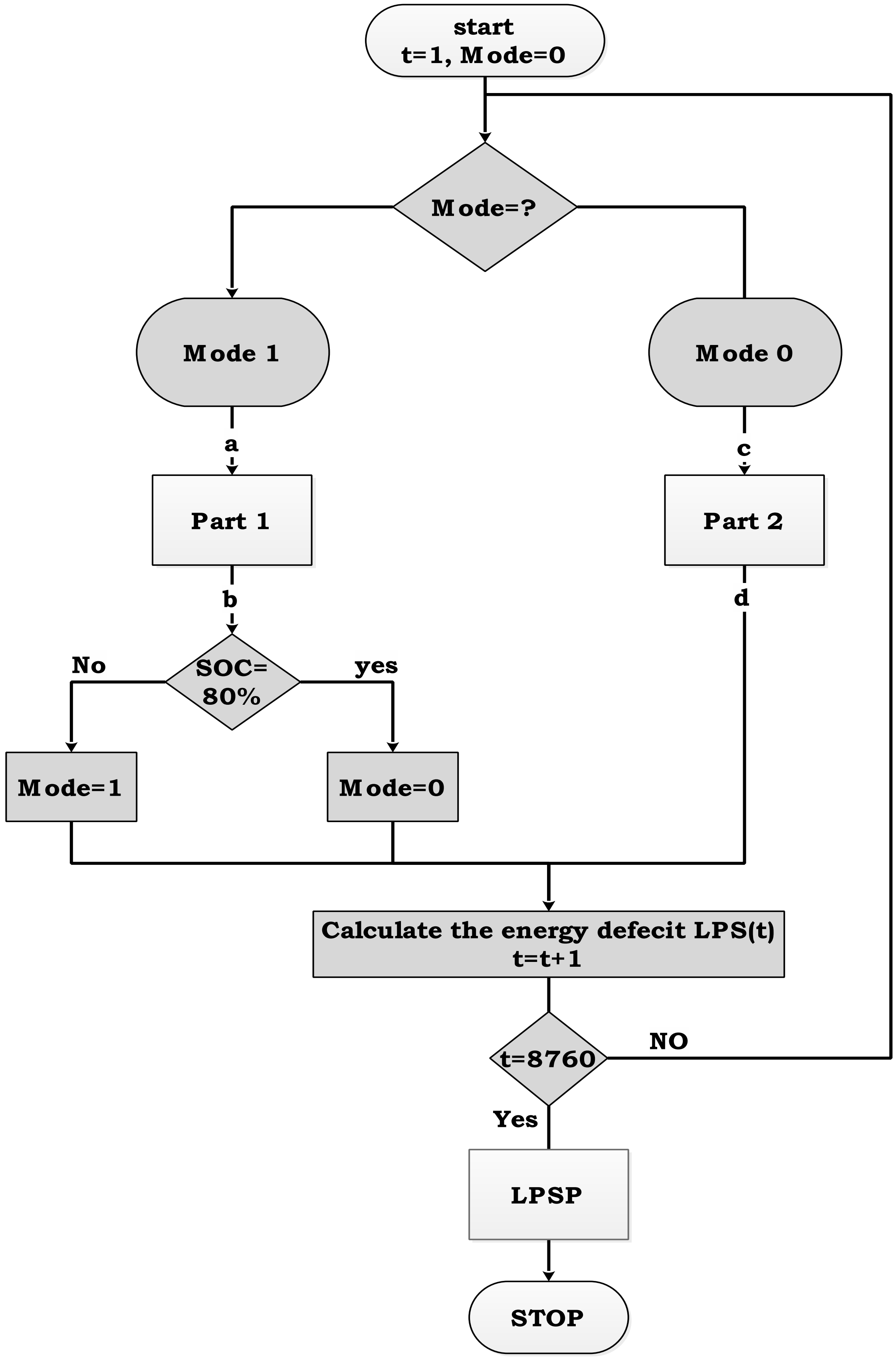


Figure 4-4 Cycle-charging strategy flowchart

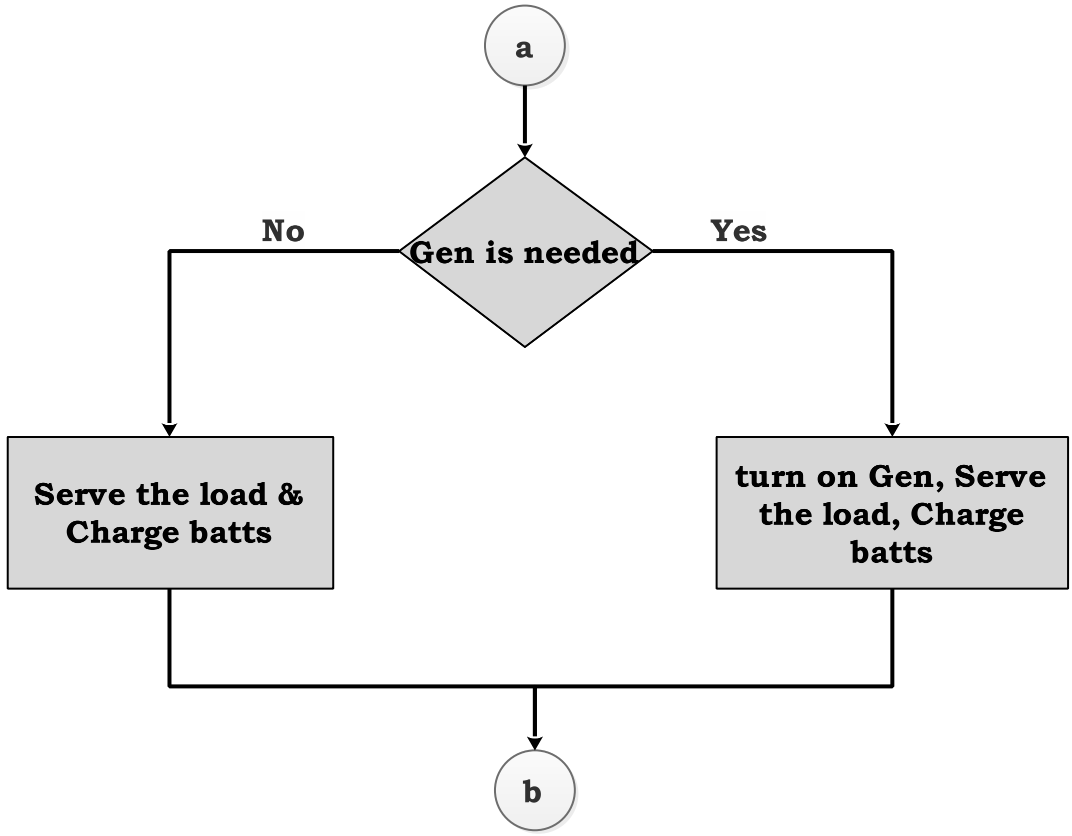


Figure 4-5 The sub strategy (Part 1) flowchart.

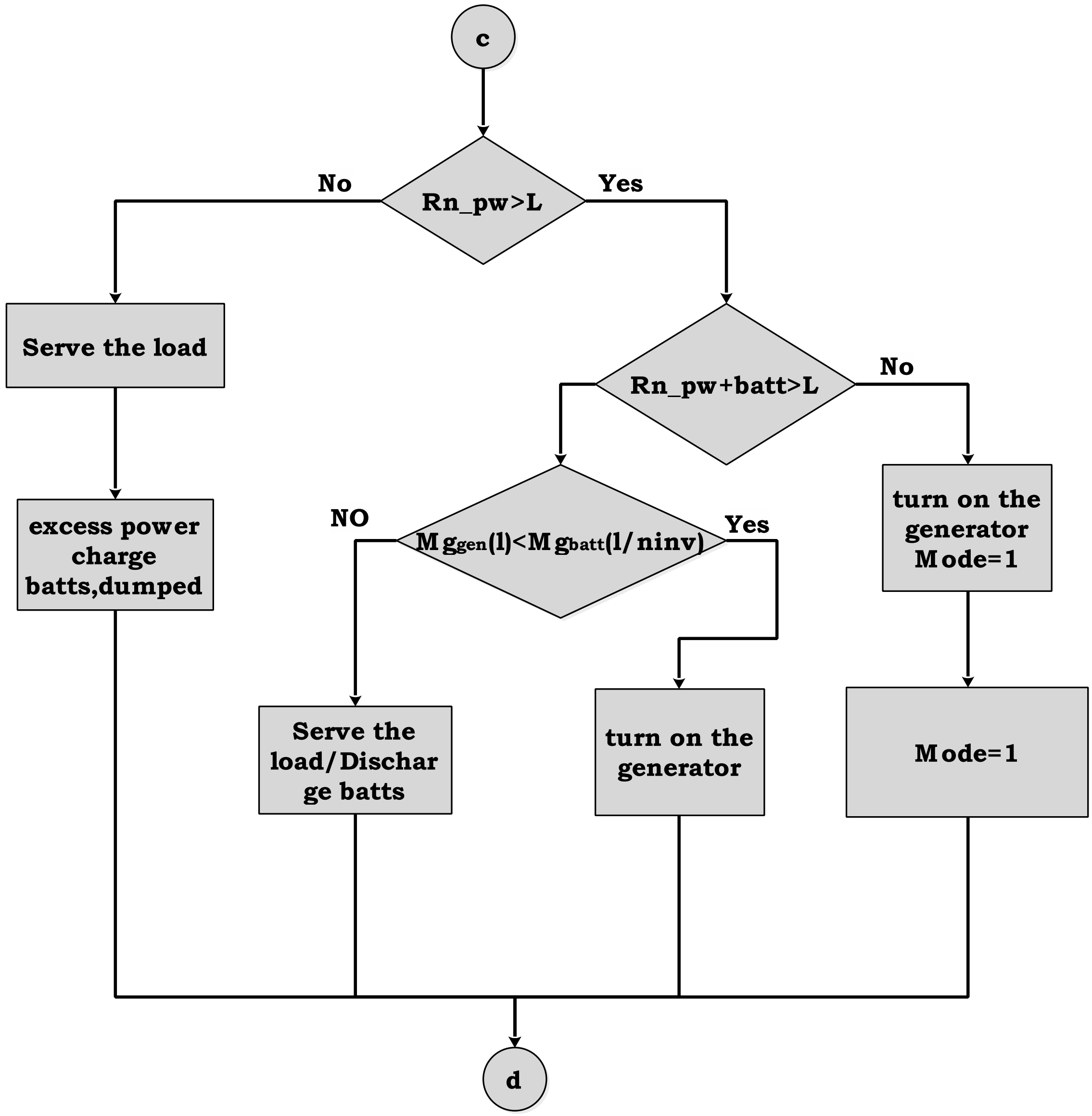


Figure 4-6 The sub strategy (Part 2) flowchart.

4.8.2 The Load-Following

Under the load-following (LF) (Figure 4-7); the battery bank can be charged by the excess energy and the generator will goes ON if it is necessary only to serve the load not to charge the battery bank.

The criterion of marginal cost is also considered here but the marginal cost is exactly the wear cost, it is also noticed that the marginal cost for the battery is calculated for the inverted load minus the total renewable output i.e. when the renewable output and the battery bank are able to serve the load, the system has two choices: either serving the load by the total renewable output and the energy stored in the batteries or serve the load by the generator and the renewable output and the excess energy goes to the battery bank, in that case the system will make a decision by comparing the value of the following functions:

$$marg_{gen}(load) = C_{gen,ma} \times load + C_{gen,fixed}$$
$$marg_{batt}(load) = \left(C_{bw} + C_{b,n}\right) \times \frac{load}{\eta_{inv}} \qquad [\$/hour] \tag{4-13}$$

If $marg_{batt}(load) < marg_{gen}(load)$ then the load is served by the renewable outputs and the battery bank, otherwise the generator is ON where its output is exactly equal to the demand (load) and any excess energy from the generator or the nondispatchable sources will charge the batteries.

4.9 Economic Modeling

Economic modeling is exactly the same with that of Homer discussed earlier; the capital cost, replacement cost, operating and maintenance cost are also the same whereas the search space is larger than earlier since TLBO has the ability to find the global minimum in large search spaces.

4.10 The fitness function

The criterion for the TLBO to know which configuration is the fittest is defined as:

$$f(x) = MIN\left(f_{CC}(x), f_{LF}(x)\right)$$
$$\boldsymbol{f_i(x) = \sqrt{TNPC^2(i) + 10^{10} \times LPSP(i)}} \tag{4-14}$$

The fitness function was considered as a vector whose components are the TNPC (total net present cost) and the LPSP (loss of power supply probability), but since the change of the LPSP is too small with respect to the TNPC, its value were not squared but rather multiplied by a huge factor (10^{10}) in order to be significant enough against the COE because the LPSP determines the feasibility of the system and the COE represents its economic factor.

The fitness value of each configuration is the smallest value between fitness values for the cycle-charging strategy and the load-following.

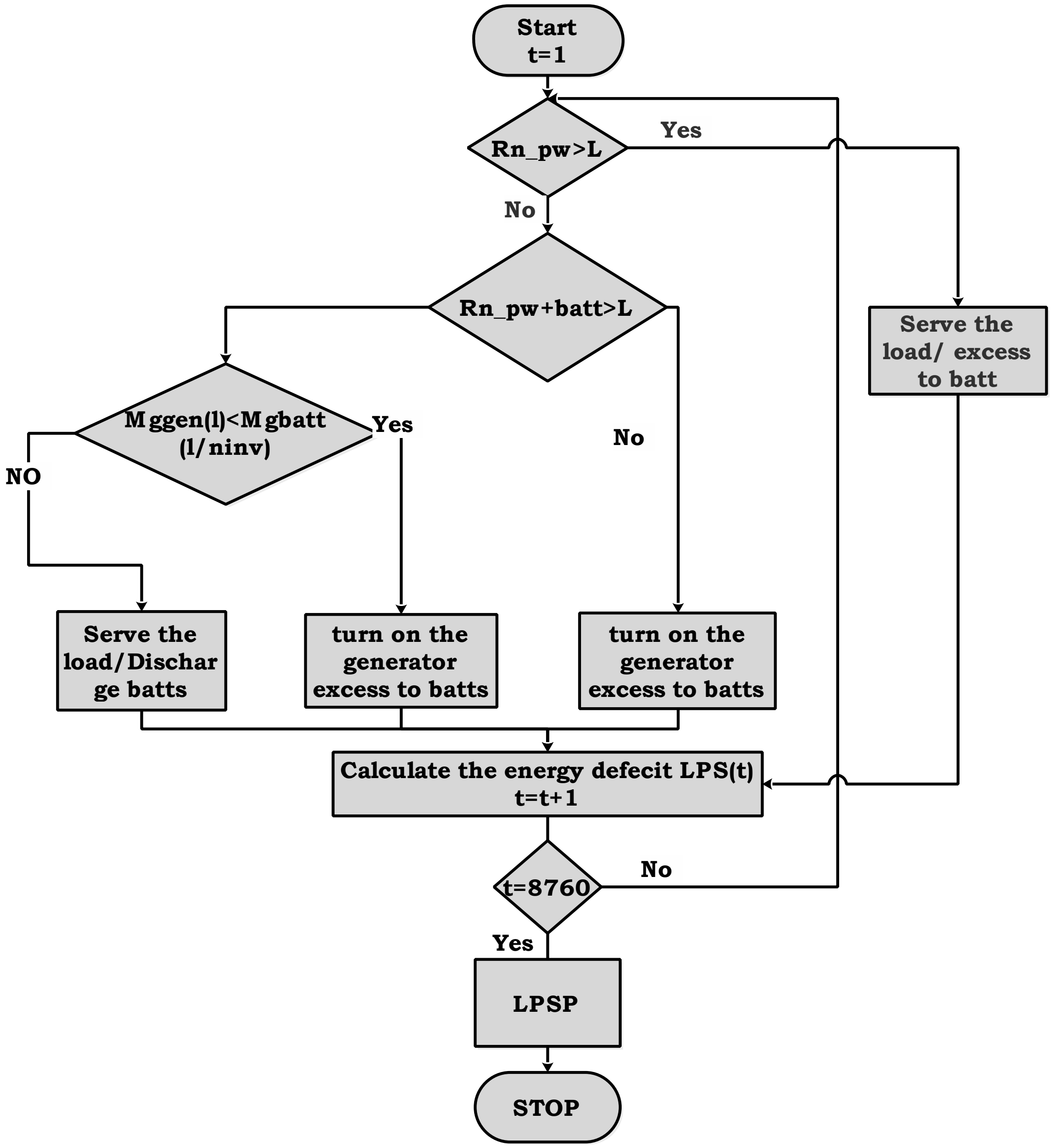


Figure 4-7 The load-following strategy flowchart.

4.10.1 <u>Sizing the converter/inverter</u>

The size of the inverter/converter does not affect the LPSP function it affects only the TNPC. In fact the size of the converter/inverter is determined after the last time step and it is given as the maximum power that travels from DC bus to the AC bus or vice versa.

However, another method inspired from Homer results is suggested which is:

- If the size of the converter is less than the inverter size: rerun the dispatch strategy and if inversed power exceeds the limit (size of the converter) switch ON the generator and charge the batteries by the renewable output power, this process occurs only in the cycle-charging.
- For the load-following dispatch strategy: rerun the dispatch strategy and don't let the inversed power exceeds the old size decremented, if that happens switch ON the generator.

4.11 The optimization algorithm (TLBO) [56]

The TLBO starts with an initial population which is generated randomly in the search space of the decision variables; then it improves its population through mathematical concepts to reach in the end its global minimum or the fittest solution ever.

The suggested TLBO for the optimization of hybrid systems was developed from[57][58][59][60][61].

The following steps describe the algorithm more precisely:

Step 0: upload the upper and lower value of each decision variable in order to limit the search space, upload the size of the population and the number of iterations.

Step 1: initialize the population in the search space found earlier.

Step 2: reinitialize any repeated solution.

Step 3: find the teacher who is the solution with the minimum fitness value.

Step 4: Teacher phase:

For a student (number *i* in the population) to learn from the teacher, the algorithm is:

```
for j=1:d  % d is the number of the decision variable(4)
```

$$x_{new}(j) = randi\big([\min\big(t(j), x_i(j)\big);\ \max(t(j), x_i(j))]\big)$$

```
End % x_new is the student with new information learned from the teacher
If f(x_new) < f(x_i) % if the the student was improved, he will keep those information
x_i = x_new;
Else x_i = x_i; %otherwise he will forgot them.
```

```
end
```

Those commands create a new student who is located between the teacher and the real student and then the best one will take the place in the population.

Step 5: again make the solutions distinct.

Step 6: Learner phase:

For a learner *i* to improve his level from his colleague *j*, a new student will be generated starting from those colleagues. If student *i* is better than *j*, the new student will be generated randomly between *i* and the limits of the search space, otherwise it will be generated between the two students.

Step 7: again remove any duplication in the population.

Step 8: find the teacher in order to be used in the next iteration or defined as the final solution.

Step 9: If the maximum number of iteration is reached stop the algorithm, otherwise return to step 4.

The algorithm flowcharts is shown in Figure 4-8.

The teacher phase and learner phase is shown in Figure 4-9, Figure 4-10 respectively.

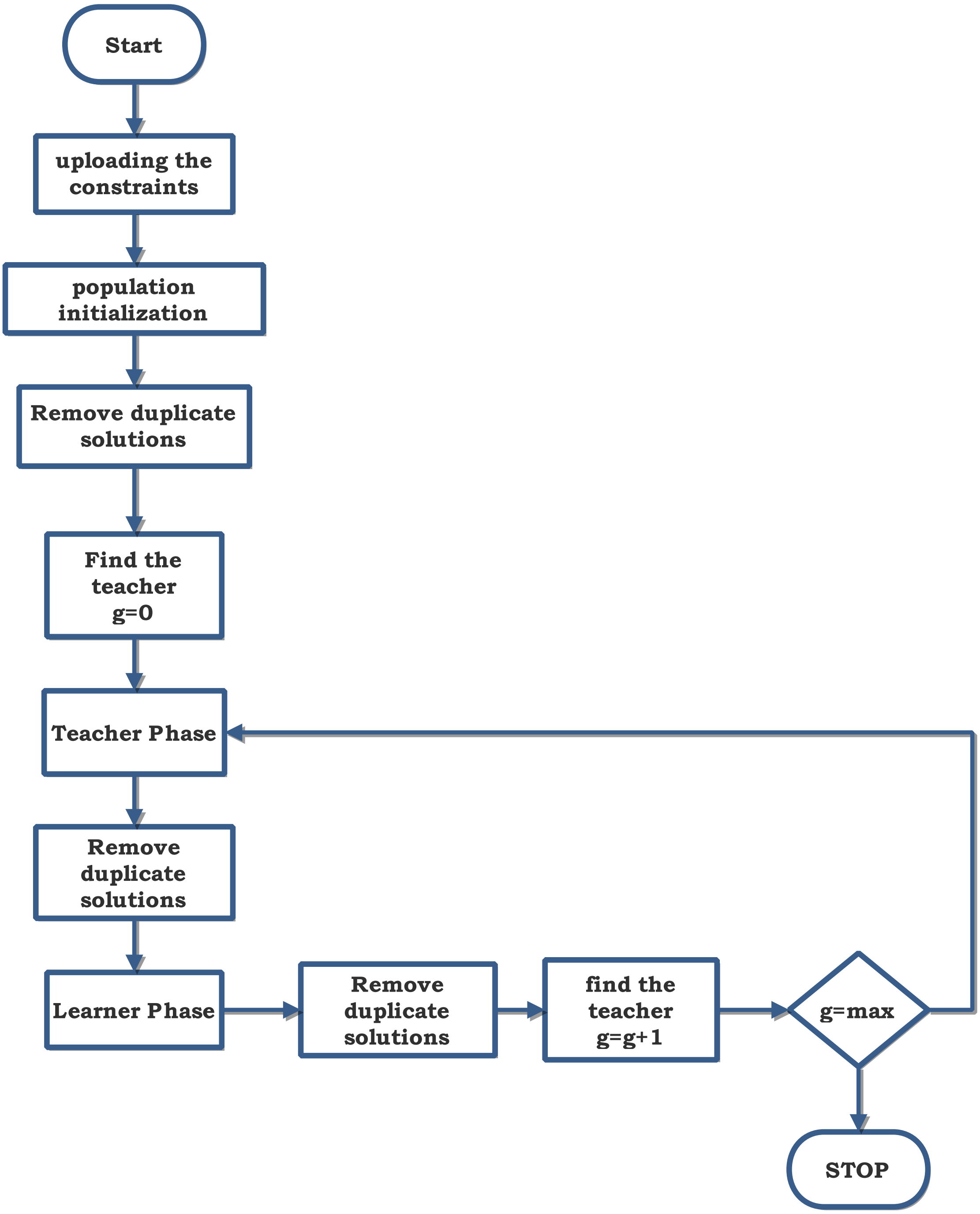


Figure 4-8 The main TLBO algorithm.

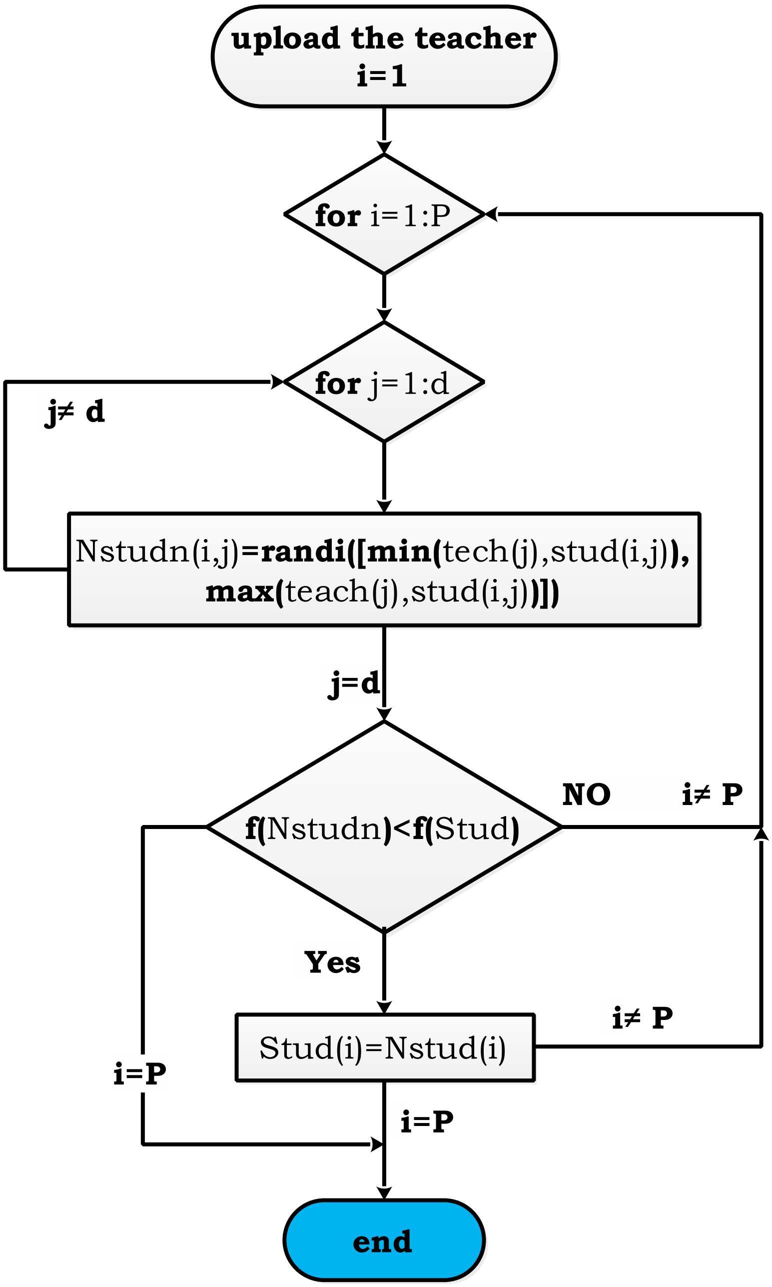


Figure 4-9 The teacher phase.

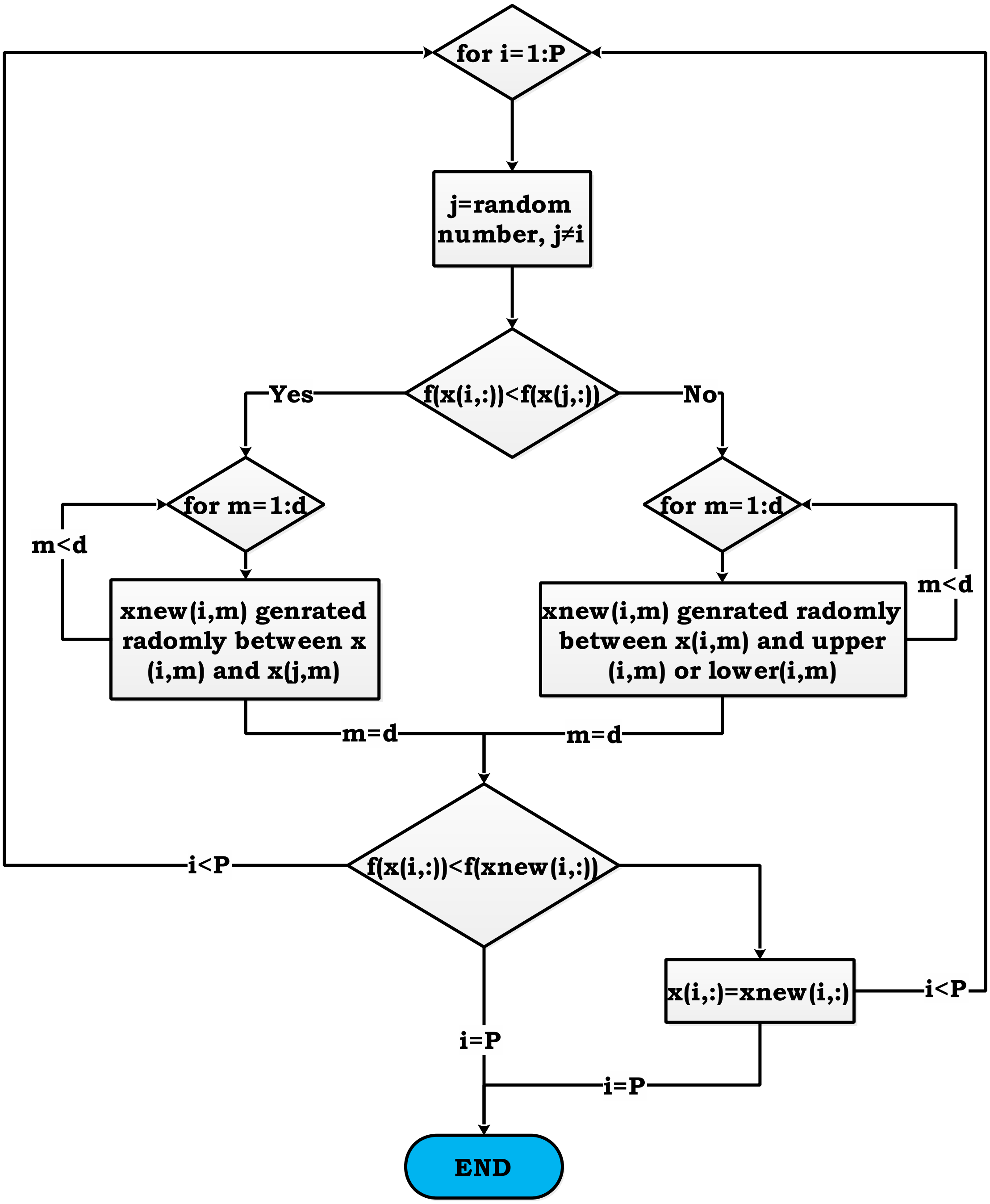


Figure 4-10 The learner phase.

4.12 Results and Discussion

The TLBO was executed in an i5 PC with a 4GB RAM, the number of iteration was taken as 10 because the search space is not so large and the population size is 50.

Shows the search space that includes the ranges of each component.

Table 4.1 TLBO search Space.

WXL1	PV	batteries	Generator(10KWh)
0,1,…20	0,1,…20	0,1,…100	0,1

Table 4.2 shows the ten optimum solutions obtained.

Table 4.2 TLBO iterations teachers.

BW XL1		Batts	Con/Inv Kw	Gen Kw	LPSP	TNPC	Oph	Fuel [liter]	strateg y
3	3	33	4	10	0	80201	2567	3150.1	LF
4	5	34	5	10	0	79846	1012	1239.2	LF
3	5	34	5	10	0	78918	1440	1752.5	LF
3	5	29	5	10	0	78839	1573	1910.9	LF
3	5	30	5	10	0	78839	1542	1873.2	LF
3	**5**	**27**	**5**	**10**	**0**	**78753**	**1636**	**1985.5**	**LF**
3	**5**	**27**	**5**	**10**	**0**	**78753**	**1636**	**1985.5**	**LF**
3	**5**	**27**	**5**	**10**	**0**	**78753**	**1636**	**1985.5**	**LF**
3	**5**	**27**	**5**	**10**	**0**	**78753**	**1636**	**1985.5**	**LF**
3	**5**	**27**	**5**	**10**	**0**	**78753**	**1636**	**1985.5**	**LF**

The results in the above table are not ranked according to their TNPCs like Homer but they are the best solutions gotten in the ten iterations. The last 5 solutions are identical because after the second iteration the algorithm didn't find any solution better.

Figure 4-11 shows results of Homer for the same inputs.

Architecture						Cost	Gen10	
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch	NPC ($)	Fuel (L)	Hours
5.0	3	10	22	4	LF	$ 79,166	2,579	2,131
6.0		10	34	4	CC	$ 81,926	4,311	2,385
	4	10	21	4	LF	$ 84,910	4,751	3,882
		10	22	3	CC	$ 90,027	8,576	5,133
		10			CC	$ 95,808	10,850	8,760

Figure 4-11 HOMER ‘s optimization results.

In order to specify the differences in the results between Homer and TLBO, the system was optimized with each dispatch strategy alone. Table 4.3 shows the optimization results of TLBO for the load-following, Figure 4-12 also do that but with HOMER.

Table 4.3 TLBO optimization results for the load-following strategy.

BWXL1	PV	Batts	Con/Inv Kw	Gen Kw	TNPC [$]	Oph	Fuel [liter]	LPSP	Dispatch Strategy
4	5	27	5	10	79603	1204	1466.9	0	LF
4	5	27	5	10	79603	1204	1466.9	0	LF
3	5	33	5	10	78889	1459	1774.1	0	LF
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**
3	**5**	**27**	**5**	**10**	**78753**	**1636**	**1985.5**	**0**	**LF**

Architecture						Cost	Gen10	
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch	NPC ($)	Fuel (L)	Hours
5.0	3	10	22	4	LF	$79,166	2,579	2,131
6.0		10	22	4	LF	$84,175	4,877	4,003
	5	10	23	4	LF	$84,999	3,949	3,220
		10	22	3	LF	$95,003	9,167	7,352
		10			LF	$95,808	10,850	8,760

Figure 4-12 HOMER's optimization results for load-following strategy.

In the load-following strategy, the results are different and that returns to the difference in the power management or the control strategy, the optimal solution for the TLBO has a TNPC smaller than the TNPC of the optimal solution of HOMER.

To expand the study, the first configuration (3 wind turbine/ 5 PV/ 27 batteries/ Gen) was simulated alone in both Matlab and Homer,Table 4.4 and Table 4.5 show the nuance between the two.

As the tables show, the differences are in:

- The replacement cost of the generator which returns to the difference in the number of operating hours i.e. HOMER's operating hours is more than those been in the MATLAB simulation.
- The fuel cost, the O&M cost and the salvage cost of the generator which also returns to the number of operating hours.
- The replacement cost and the salvage cost of the battery bank, since the generator's operating hours of MATLAB simulation is less than those of HOMER, the use of batteries in MATLAB simulation is more than HOMER and definitely the expected life for the battery is less, therefore the replacement cost should be higher as well as the salvage cost.

Table 4.6 shows the optimization results of TLBO for the cycle-charging, Figure 4-13 also does that but with HOMER:

Table 4.4 MATLAB simulation and HOMER simulation for the same configuration (LF).

	TNPC ($)	OPh (hours)	Fuel (liters)	Expected battery life (years)	Operating cost ($)
Homer	79987	1949	2359	4.779	10392
Matlab	78753	1636	1985.5	4.259	9165.1

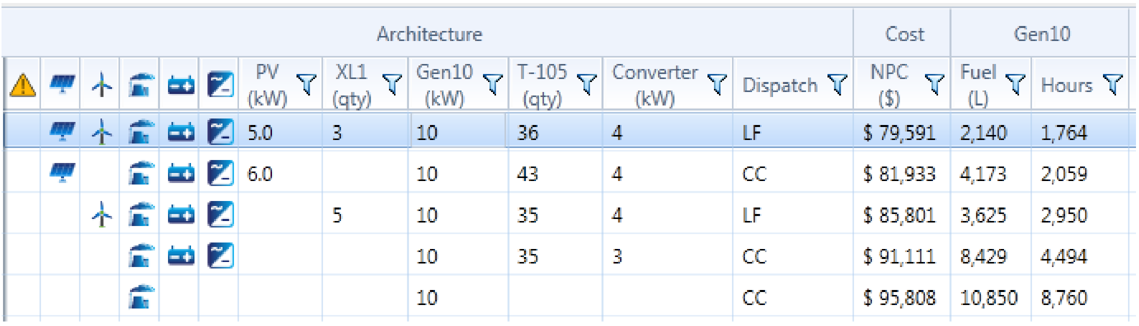
Table 4.5 Economic summary.

	Component	**Capital**	**Replacement**	**O&M**	**Fuel**	**Salvage**	**Total**
HOMER	PV	15000	0	6 6	0	0	15646
	BWC XL.1	13500	4304	776	0	2426	16154
	Gen	5000	6641	7574	4588	892	22911
	T-105	5940	14085	1396	0	1094	20327
	Co verter	3750	1591	0	0	299	5042
	System	43190	26621	10392	4588	4711	80080
MATLAB	PV	15000	0	646.52	0	0	15646.52
	BWC XL.1	13500	4305.8	775.83	0	2426.87	16154.76
	Gen	5000	4714.8	6346.25	3851	327.58	19584.47
	T-105	5940	15174	1396.48	0	1853.67	20656.81
	Converter	3750	1591.6	0	0	299.61	5041.99
	System	43190	25786	9165.1	3851	3239.4	78752.70

Table 4.6 TLBO optimization results for the cycle-charging strategy.

BWXL1	PV	Batts	Con/Inv Kw	Gen Kw	TNPC [$]	Oph	Fuel [liter]	LPSP	Dispatch strategy
5	3	53	5	10	83941	720	1648.4	0	CC
3	4	56	5	10	80506	914	2224.1	0	CC
3	4	54	5	10	80183	933	2231.2	0	CC
3	4	51	5	10	79806	967	2251.7	0	CC
3	5	45	4	10	79671	918	1848.4	0	CC
3	**4**	**47**	**4**	**10**	**78929.1**	**1063**	**2334.9**	**0**	**CC**
3	**4**	**47**	**4**	**10**	**78929.1**	**1063**	**2334.9**	**0**	**CC**

3	**4**	**47**	**4**	**10**	**78929.1**	**1063**	**2334.9**	**0**	**CC**
3	**4**	**47**	**4**	**10**	**78929.1**	**1063**	**2334.9**	**0**	**CC**
3	**4**	**47**	**4**	**10**	**78929.1**	**1063**	**2334.9**	**0**	**CC**



Architecture						Cost	Gen10	
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch	NPC ($)	Fuel (L)	Hours
5.0	3	10	36	4	LF	$ 79,591	2,140	1,764
6.0		10	43	4	CC	$ 81,933	4,173	2,059
	5	10	35	4	LF	$ 85,801	3,625	2,950
		10	35	3	CC	$ 91,111	8,429	4,494
		10			CC	$ 95,808	10,850	8,760

Figure 4-13 HOMER's optimization results for the cycle-charging strategy.

A notice on HOMER which can be deduced is the possibility to fall in local optima, Figure 4-13 shows the results for HOMER with battery search space (0, 35 …45):

The beginner user of HOMER has no experience in choosing the right search space, and if he chooses a large search space like the one associated with TLBO the simulation may take a long time to end.

To determine the source of that variance between TLBO and HOMER, the optimal solution found by TLBO is simulated by HOMER and the cycle charging strategy used in TLBO, Table 4.7Table 4.8 summarize the differences.

Table 4.7 MATLAB simulation and HOMER simulation (CC).

	TNPC ($)	OPh (hours)	Fuel (liters)	Expected battery life (years)	O erating cost ($
Homer	80397	1087	2021	6.0477	2596
Matlab	79875.79	1063	2334.84	5.5902	9165.1

Table 4.8 Economic results (3XL1/ 5 PV/ 4 Kw converter/ 47 batteries/ Generatror)

	Component	Capital	Rep acement	O&M	Fuel	Salvage	Total
HOMER	PV	15000	0	646	0	0	15646
	BWC XL.1	13500	4304	776	0	2426	16154
	Gen	5000	2272	4216	3919	226	15181
	T-105	10340	18757	2430	0	2146	29382
	Converter	3000	1273	0	0	240	4033
	System	46840	26606	8068	3919	5036	80397
MATLAB	PV	15000	0	646.52	0	0	15646.52
	BWC XL.1	13500	4305.81	775.83	0	2426.87	16154.77
	Gen	5000	1804.64	3262.35	3408.88	717.08	12758.79
	T-105	10340	19819.57	2430.92	0	1308.33	31282.16
	Converter	3000	1273.25	0	0	239.69	4033.56
	System	43840	27203.27	7115.61	3408.88	4691.97	79875.8

Obviously TLBO solutions are less costly than HOMER solutions, the results are not the same and that is not due to the optimization algorithm but rather due to some facts related to the control strategy itself which are:

- Homer considers the self-discharging of the battery bank.
- The amount of power generated to charge the batteries in the cycle-charging in Homer depends on the future renewable outputs and that’s the prediction control strategy.

In the cycle charging the main reason for the inequality of the results is the prediction feature in the control strategy of Homer. As described earlier the criterion for running the generator or consuming the batteries energy is the marginal cost. Even though sometimes the marginal cost of the battery bank is less than the one of the generator, Homer decides to run the generator in order to minimize the size of the inverter, a technique used in TLBO inspired from that was described in section 4.10. Table 4.9 shows how the prediction part of the control strategy affects the results.

Table 4.9 (3XL1/ 5 PV/ 4 Kw converter/ 47 batteries/ Generatror) states between the 92nd hour and the 100th hour.

Common information					HOMER			MATLAB		
Load	Gmag	MaxCh	Trpw	B/G	Gout	Batin	SOC	Gout	SOC	Batin
1.86	0.51	3.36	0.98	B	0	-1.08	62.52	0	82.84	0
3.58	0.99	3.36	0.71	G	5.97	2.86	66.68	7.64	88.14	3.36
2.94	0.81	3.36	0.75	B	5.29	2.87	70.84	0	83.84	0
2.69	0.74	3.36	0.30	B	5.45	2.78	74.89	0	79.23	0
2.52	0.70	3.36	0.27	B	5.30	2.78	78.92	0	74.91	0
2.05	0.57	3.36	0.64	B	5.07	3.36	83.81	0	72.11	0
1.89	0.52	3.36	1.27	B	0	-0.83	82.39	0	70.69	0
0.49	0.14	3.36	0.65	B	0	0.10	82.54	0	70.99	0.19
0.65	0.18	3.36	0.32	B	0	-0.41	81.84	0	70.29	0

Gmag: is the marginal cost of the generator.

MaxCh: the maximum charge power of the battery bank.

Trpw: total renewable output= Wind power+Solar power

B/G: which is the least marginal cost, is it the one of the batteries or generator.

Gout: the power output of the generator.

Batin: the power that goes into the battery bank.

SOC: state of charge.

As shown in the above table, when the generator has the least marginal cost Homer control strategy switches ON the generator as well as the control strategy used in the TLBO. The difference between the two strategies appears here, when the generator is the cheapest to serve the load HOMER generate a power for that and an extra power to charge which is shown in the second line in the table, even though the battery bank can receives 3.36 Kw as an input power the control strategy gives only 2.86 Kw since the future renewable outputs are not enough to fit the load. the amount of the extra power depends on the future renewable power outputs. After that the generator continues to serve the load because the step point is not reached yet. The control strategy used in TLBO produce exactly the maximum allowable charge power.

- Homer has a specific strategy to minimize the size of the converter/inverter component.

As mentioned above Homer minimizes the size of the inverter/converter component through a specific strategy , the latter is not published neither in scientific papers nor in Homer's help tool, Table 4.9 shows how Homer behaves in a different way :

Normally in a lack of renewable power to meet the load, Homer should make a decision either to run the generator to cover the lack of power or to use the battery content power. As discussed in section 3.4, a decision like that depends on the marginal cost energy i.e. the generator is ON if it is less costly than using the battery energy, otherwise the battery bank will be used to cover the lack of power but after experiencing HOMER results of many systems it is observed that sometimes the battery bank has the lowest marginal cost and Homer decided rather to use the generator because using the battery bank will require a bigger size of the inverter i.e. for example the inverter should be of size 5 Kw in a place of 4 KW.

Another important point will appear after comparing the results in Table 4.2, Figure 4-11 and Table 4.6 which are:

HOMER results are ranked from lowest TNPC to the highest TNPC.

TLBO results are ranked in the same way but between each two optimum solutions it might exist better than the previous or better than both, because TLBO is a metaheuristic method i.e. its purpose is finding the optimal solution the first found optimum solutions are just a try no more and they can be bad solutions.

This point is obvious when seeing that TLBO in ten iterations (Table 4.2) didn’t find any solution with CC strategy but there are solutions in Table 4.6 better than them, one can say it is just luck however it proves that the search space of the LF is less costly than the CC search space as the case with HOMER in Figure 4-11, as said before HOMER shows the results categorizing them into groups so the first group is (PV/XL1/T105/Gen) with LF strategy and this is the case with TLBO.

4.13 Conclusion

The renewable energy resources hybridized with fossil fuel generators fit the demand side with an efficient and reliable power. In this chapter the optimal design of a stand-alone hybrid system using TLBO is presented. This design was implemented considering the LPSP reliability index, for wind- solar- diesel system and the total net present cost of the project. The obtained results were compared to those of HOMER and they are less costly which indicates the non-optimality of the predictive control strategy of Homer but that is not more important than the possibility to be tricked by local optima with homer whereas with TLBO the globality is guaranteed.

CONCLUSION

This report summarize the important aspects and techniques involved in the smart grid starting from the requirement of a grid to be smart, passing through smart meters general functions, the role of PMU in Wide area monitoring , intelligence electronic devices (IEDs), the communication infrastructure of smart grid and ending by transmission system and Wide-Area Measurement Systems.

This project accomplished two objectives in the second chapter. First, the teaching-learning based optimization method is investigated and a proposed binary version is developed. Second, the developed method is applied for determining optimal locations for PMUs to ensure complete system observability.

TLBO has a different way to improve the level of the population, first it raises the class level when the best student teaches the others , second it allows students to interact with each other developing their skills randomly. So TLBO tries first to find the optimal solution in the vicinity of the teacher like ACO after that it searches for better solutions that could be between the others like GA and PSO. BTLBO has been developed in this project starting from the origin TLBO in the real space.

Placement of PMUs can be carried out using different criteria depending on the objective of the investigator. In this report, the main focus is to make the entire system observable by an optimal placement of PMUs. Various scenarios are considered where the system is first assumed to be observed by PMUs only. While this appears impractical today, it may very well be the case in a few years when these devices become standard equipment at substations. Next, the placement problem is considered for a system with existing measurements, some of which may be PMUs. Case studies which are carried out on IEEE test systems indicate that strategically placing PMUs at roughly one third of the system buses, the entire system can be made observable with only PMUs. Furthermore, zero injections, and conventional measurements which can significantly reduce the required number of PMUs for a given system.

It is not unusual to have additional considerations apart from strict observability criterion, when deciding on the location of PMUs. These considerations can be taken into account by appropriately modifying the optimization problem which is formulated in this report. This can be done as an extension to this project in the future. On the other hand, this report assumes that all PMUs are free of defects and their failure is not considered as a possibility. In practice, this assumption may not always hold true due to unexpected failures in these devices or gross errors introduced by the noise in the communication system. Therefore, it might be prudent as future challenge to consider the case of PMUs failure as a possible contingency in the formulation and solution of the PMU placement problem and this can be done if the redundancy is considered in the formulation of the problem. Considering the economic effect of installing a PMU on each bus might be another term to generalize the study and that can be done through changing the objective function by adding an economic weight to each bus, each bus has a number of branches, therefore it needs a certain type of PMU that has the same number of channels. For the study of the TLBO itself the speed of convergence is needed to be understood for other applications.

The integration of renewable energy resources through the most well-known tool in that field "HOMER", the strength of Homer is in its accurate modeling of the whole system firstly and secondly; its control strategy which is built on the notion of the set point of charge of the battery are all studied in this report (chapter 3). Homer has two dispatch strategies: Load-following and Cycle-charging, in the load-following the set point must be 0% whereas in the cycle-charging the set point is adjustable (recommended 80%). The advantage of Homer against all metaheuristic algorithms is that HOMER simulates the whole search space and ranks the feasible solutions according to their TNPCs.

The study of HOMER is accomplished through the optimization of a hybrid standalone Wind/Solar/Diesel based energy system in the site of In Salah. The region proves that it possesses a large potential of both solar and wind energies which can be a better alternative sources of electricity in remote areas.

The robustance of the solution is concluded from the sensitivity analysis tool of HOMER which allows to detect the change of the results according to the changing of sensitivity parameters.

To increase the certainty of the powerfulness of the area and to study the heart of Homer, another way is suggested for optimizing hybrid system which is the optimization by TLBO (Chapter 4). A proposed TLBO is developed for optimizing hybrid systems. The fitness function was taken as combination of TNPC and LPSP index, TLBO in the end proves its great ability in the optimization, the main advantage of TLBO over Homer is the globality certainty. Metaheuristic methods characterized by their ability to reach the global optimum even if the search space is large. The reliability of a configuration is computed by two control strategies like HOMER: load-following and cycle-charging but with some differences. The used control strategies in TLBO provide a less TNPC than those of HOMER but that doesn't prove its winning, instead it gives an idea to study the optimality of the control strategies in further projects and it shows that the prediction control strategy is not always suitable.

Smart grid is a wide search field, this report is a small work in the side of power delivering and consuming. The communication part which is the basic infrastructure of smart grid was not included and it can be studied in further work. The power management and optimizing the use of electrical energy using the recent technologies can be also a target in future works.

Appendix

Test functions:

- Ackley's function:

$$f(x) = -a.\exp\left(-b.\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i\right) + a + \exp(1)$$

$$a = 20, b = 0.2, c = 2\pi, -32.768 \leq x_i \leq 32.768\,, i = 1, \dots, n$$

- Griewank's function:

$$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, -600 \leq x_i \leq 600, i = 1, .. n$$

- Rosenbrock's function:

$$f(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]\,,\ -2.048 \leq x_i \leq 2.048, i = 1, \dots, n$$

- Sphere function:

$$f(x) = \sum_{i=1}^{n} x_i^2\,, -100 \leq x_i \leq 10, i = 1, \dots, n$$

References

[1] B. Nadu., M. C. Valenti, A. Feliachi, “Communication delays in wide area measurement systems”, Southeastern Symposium on System Theory, (2002), pp. 118-122.

[2] Waheed Ur Rahman, Muhammad Ali, Amjad Ullah, Hafeez Ur Rahman, Majid Iqbal, Haseeb Ahmad, Adnan Zeb, Zeeshan Ali, M. Ahsan Shahzad, Beenish, “Advancement in Wide Area Monitoring Protection and Control Using PMU’s Model in MATLAB/SIMULINK”, Smart Grid and Renewable Energy, No 3 , (2012) , 294-307

[3] C. D. Barley and C. B.Winn, “Optimal dispatch strategy in remote hybrid power systems”, Solar Energy, Vol 58, (1996), pp 165–179.

[4] Barley CD, Winn CB, Flowers L, Green HJ, “Optimal control of remote hybrid power systems”. Part I. Simplified model. In: Proceedings of WindPower’95, (1995).

[5] HOGA (Hybrid Optimization by Genetic Algorithms), available from: http://personal.unizar.es/rdufo

[6] HOMER (The Hybrid Optimization Model for Electric Renewables). Available from: http://www.nrel/gov/HOMER.

[7] Christian Sasse et al, “European smart grids technology platform”, Office for Official Publications of the European Communities, (2006), pp 44.

[8] J. Ekanayake, K. Liyanage, J. Wu, A. Yokoyama, N. Jenkins, “Smart Grid Technology And Applications” , Wiley, (2012), pp 2-12, pp 45-116.

[9] Iordanis Koutsopoulos, Leandros Tassiulas, “Control and optimization meet the smart power grid: scheduling of power demands for optimal energy management”, Energy-Efficient Computing and Networking, (2011), pp 41-50.

[10] James Momoh, “Smart grid fundamentals of design and analysis”, Wiley & Sons (2012), pp 2-6.

[11] “Oracle Solutions For Smart Grid”, (December 2010), available from: http://www.oracle.com

[12] Schneider Electric, SCADA Systems, white paper, (March 2012).

[13] http://www.wikipedia.com

[14] PA Boyd GB Parker DD Hatley, “Load Reduction, Demand Response and Energy Efficient Technologies and Strategies”, Pacific Northwest National Laboratory, (November 2008).

[15] Phillip Yeung, “Reducing Energy Costs with Peak Shaving in Industrial Environments”, Schneider electric, (September 2007).

[16] NERC Resources Subcommittee, “Balancing And Frequency Control”, NREC, (January 26, 2011).

[17] Deyu Cai, “Wide Area Monitoring, Protection And Control In The Future Great Britain Power System”, PhD in Electrical and Electronic Engineering thesis, University of Manchester, (2012).

[18] Rahul H. Shewale , Bala Krishna Kethineni, Uma P Balaraju, S. K. Bhil , Prashant D More,”Optimal placement of phasor measurement unit for power system observability by heuristic search method”, International Journal of Advanced Technology & Engineering Research, Vol 2 No 2, (may 2012), pp 128-133.

[19] James Ross Altman, “A Practical Comprehensive Approach to PMU Placement for Full Observability”, thesis of master of science in electrical engineering, Virginia Polytechnic Institute and State University (January 28, 2007).

[20] A.G. Phadke and J. S. Thorp, “Synchronized Phasor Measurements and Their Applications”, New York, Springer, 2008.

[21] Singh, N.K. Sharma, A.N. Tiwari, K.S. Verma, and S.N. Singh. “Applications of phasor measurement units (PMUs) in electric power system networks incorporated with FACTS controllers”, International Journal of Engineering, Science and Technology Vol 3 No 3, (2011), pp 64-82.

[22] Volker Lohmann, “New strategies for substation control, protection and access to information”, 16th International Conference and Exhibition on Electricity Distribution ,IEEE Confference Publ No 482, (2001).
[23] T. L. Baldwin, L. Mili, M. B. Boisen and R. Adapa, “Power System Observability with Minimal Phasor Measurement Placement”, IEEE Transactions on Power Systems, Vol 8 No 2, (1993) , pp.707-715.
[24] Mohammad-Reza Mosavi, Amir-Ali Akhyani, Abdolreza Rahmati, “A PMU Placement Optimal Method in Power Systems using Modified ACO Algorithm and GPS Timing”, Przegląd Elektrotechniczny, (2012), pp 346-349.
[25] B. Xu, “Optimal monitoring and visualization of steady state power system operation”, Ph.D Dissertation, Texas A&M University, (Aug 2006).
[26] R. Venkata Rao and Vivek Patel, “An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems”, International Journal of Industrial Engineering Computations, Vol 3 No 4, 2012, pp 535-560.
[27] Devesh Dua, Sanjay Dambhare, Rajeev Kumar Gajbhiye, “Optimal Multistage Scheduling of PMU Placement: An ILP Approach”, IEEE transactions on power delivery, Vol 23 No 4, (October 2008), pp 1812-1820.
[28] Sanjay Dambhare, Devesh Dua, Rajeev Kumar Gajbhiye, S. A. Soman, “Optimal Zero Injection Considerations in PMU Placement: An ILP Approach”, Glasgow, Scotland, (July 14-18, 2008).
[29] Mohammad Shahraeini, M. Hossein Javidi, “A Survey on Topological Observability of Power Systems”, Vol 3, IEEE, (2011), pp 373-376.
[30] Xu Bei, Yeo Jun Yoon and Ali Abur, “Optimal placement and utilization of phasor measurements for state estimation”, PSERC, (2005).
[31] Xu, B., & Abur, A, “Optimal placement of phasor measurement units for state
estimation”. Final project report, PSERC (2005).

[32] B. Mohammadi-Ivatloo , “Optimal Placement of PMUs for Power System Observability Using Topology Based Formulated Algorithms”, Journal of Applied Sciences, Vol 9, (2009), pp 2463-2468.

[33] Jiangnon.P,.S., yuanzhang, and H,F wang, “Optimal Placement for full Network Observability using Tabu Search Algorithm”, International Journal of Electrical Power & Energy Systems , Vol 28 No 4, (May 2006), pp 223–231.

[34] Melosovic,B M. Begovic, “Nondominated sorting genetic algorithm for optimal phasor measurement placement”, Power Systems, IEEE Transactions, Vol 18, (2003), pp 69-75.

[35] Ganga Reddy Tankasala, Sridhar Sanisetty, Varun Kumar Vala, “Optimal Placement of Phasor Measurement Units for State Estimation using Artificial Intelligence Techniques”, International Journal of Scientific & Engineering Research, Vol 3 No 2, (February 2012).

[36] Department of Energy, the American Recovery and Reinvestment Act of 2009 , “Factors Affecting PMU Installation Costs” , (September 2014).

[37] V. A. Graham and K. G. T. Hollands, A method to generate synthetic hourly solar

radiation globally, Solar Energy, Vol 44 No 6, (1990), pp 333–341.

[38] V. A. Graham, K. G. T. Hollands, and T. E. Unny, “A time series model for K, with application to global synthetic weather generation”, Solar Energy, Vol 40 No 2, (1988), pp 83-92.

[39] Rusawasatt Lutato, “Minimising Excess energy in Sizing of Hybrid Renewable Power Systems”, SCIE Journals, (2012), pp 26-36.

[40] Kashefi Kaviani, et al ,”Soft Computing in Green and Renewable Energy Systems”, Springer, (2009).

[41] Farouk Chellali, Adballah Khellaf , Adel Belouchrani , Abdelmadjid Recioui ,”A contribution in the actualization of wind map of Algeria”, Renewable and Sustainable Energy Reviews, Elsevier, Vol 15, (2011), pp 993–1002

[42] HOMER energy modeling software. National Renewable energy laboratory. Available from: http://www.homerenergy.com/.

[43] Pei Yi Lim, "Power Management Strategies for Off-Grid Hybrid Power Systems", Phd thesis, Curtin University, (October 2011).

[44] Mohammadi M, Hosseinian SH, Gharehpetian GB, "GA-based optimal sizing of microgrid and DG units under pool and hybrid electricity markets". International Journal of Electrical Power & Energy Systems, Elsevier, Vol 35 No 1, (2012), pp83-92.

[45] Hanieh Borhanazad a, Saad Mekhilef a, Velappa Gounder Ganapathy b, Mostafa Modiri-Delshad, Ali Mirtaheri , "Optimization of micro-grid system using MOPSO" , Renewable Energy, Elsevier, Vol 71, (2014), pp 295-306.

[46] Erdinc O, Uzunoglu M, "Optimum design of hybrid renewable energy systems: overview of different approaches", Renewable and Sustainable Energy Reviews, Elsevier, Vol 16 No 3 (2012), pp 1412–1425.

[47] Luna-Rubio R, Trejo-Perea M, Vargas-V azquez D, Ríos-Moreno GJ, "Optimal sizing of renewable hybrids energy systems: a review of methodologies", Solar Energy, Elsevier, Vol 86 No 4, (2012), pp 1077-1088.

[48] Lingfeng Wang, "integration of renewable energy sources:Reliability-constrained power system planning and operations using computational intelligence", thesis of Phd in Electrical Engineering, Texas A&M University, (December 2008).

[49] Bogdan, S. B. and Salameh, Z. M, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system", IEEE Transactions on Energy Conversion, Vol 11 No 2, (1996), pp 367-375.

[50] Bin, A, Hongxing Y, Shen H, Xianbo L, "Computer aided design for PV/Wind hybrid system", Renewable Energy, Elsevier, Vol 28 No 10, (2003), pp1491-1512.

[51] J. F. Manwell and J. G. McGowan, "Lead acid battery storage model for hybrid energy systems", Solar Energy, Vol 50 No 5, (1993), pp. 399–405.

[52] Said. Diaf, Djamila Diaf, Mayouf Belhamel, Mourad Haddadi, Alain Louche, "A methodology for optimal sizing of autonomous hybrid PV/wind system", Energy Policy, Elsevier, Vol 35, (2007), pp 5708-5718.

[53] Kaabeche A, Belhamel M, Ibtiouen R, "Techno-economic valuation and optimization of integrated photovoltaic/wind energy conversion system", Solar Energy, Elsevier, Vol 85 No 10, (2011), pp 2407-2420.

[54] Deshmukh MK, Deshmukh SS, "Modeling of hybrid renewable energy systems",
Renewable and Sustainable Energy Reviews, Elsevier, Vol 12 No 1, (2008), pp 235-249.

[55] Recioui.A, Bentarzi.H, Chellali.F, "Stand-alone system optimization and assessment of wind energy potential of a remote area in Algeria", International Symposium on Environment Friendly Energies in Electrical Applications, Vol 2 No 4,(November 2010).

[56] R. Venkata Rao, Vivek Patel, "Comparative performance of an elitist teaching-learning-based optimization algorithm for solving unconstrained optimization problems", International Journal of Industrial Engineering Computations, Vol 4 No1, (2013), pp 29-50.

[57] Matej C, ˇrepinšek, Shih-Hsi Liu, Luka Mernik, "A note on teaching–learning-based optimization algorithm", Information Sciences, Elsevier, Vol 212, (2012), pp 79–93.

[58] R.V. Rao, V.J. Savsani, D.P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems", Computer-Aided Design Elsevier, Vol 43 No 3, (2011), pp 303–315.

[59] R. Venkata Rao , Vivek Patel, "An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems", Scientia Iranica, Vol 20 No 3, (June 2013), pp 710–720.

[60] R.V. Rao, V.J. Savsani, D.P. Vakharia, “Teaching–Learning-Based Optimization: An optimization method for continuous non-linear large scale problems”, Information Sciences, Elsevier, Vol 183 No 1, (2012), pp 1–15.

[61] K.R. Krishnanand, Bijaya Ketan Panigrahi, P.K. Rout, and Ankita Mohapatra, “Application of Multi-Objective Teaching-Learning-Based Algorithm to an Economic Load Dispatch Problem with Incommensurable Objectives”, SEMCCO 2011, Vol 7076, (2011), pp 697–705.