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Geotechnical Option

Theme

Application of Artificial Neural Networks (ANNs) to Predict the Behavior of Reinforced Linear Pavements with Geosynthetics -Comparison with Finite Element Method-

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ملخص

البنية التحتية الأساسية، مثل الطرق والمنشآت الهندسية وممرات المطارات، تعتبر عمودًا فقريًا لنظام النقل في أي بلد وعاملاً رئيسيًا في الاستقرار الاقتصادي، نظرًا للخدمات التي تقدمها لتلبية احتياجات السكان. تتمتع الجزائر بشبكة واسعة جدًا من الطرق وممرات المطارات، يتعرض معظمها لأحمال متكررة من حركة الشاحنات الثقيلة والطائرات، مع تأثيرات ديناميكية. نتيجة لذلك، يمكن ملاحظة التدهور وانتشار التشقق في طبقات الاستهلاك، مما يؤدي إلى فقدان قدرة تحمل الأحمال في هياكل الممرات الرصفية، مما يتطلب إجراء إصلاحات و/أو تعزيز كجزء من الصيانة الروتينية أو المستمرة. أثبتت الحلول المتمثلة في إدخال طبقات التسليح الإصطناعي الأرضي مزايا مقنعة جدًا خلال تطبيقها (على مدى الثلاثين السنة الماضية). ومع ذلك، لا يزال هناك قلة (إن وجدت) في رصد سلوك أي ممر رصيف أو طريق يتم تعزيزه بهذا النوع من المواد. ولهذا السبب، يفكر الخبراء والباحثون في مجال الهندسة الجيوتقنية في إيجاد حلول وتوقع سلوك هذه البنى على مر الزمن. تقدم رسالة الماجستير هذه إسهامًا في فهم طريقة التنبؤ المعروفة باسم "الشبكات العصبية الوصطناعية "، من خلال جمع قواعد البيانات من التجارب العملية للشركات والمختبرات والمكاتب الاستثلارية، بالإضافة البنى على مر الزمن. تقدم رسالة الماجستير هذه إسهامًا في فهم طريقة التنبؤ المعروفة باسم "الشبكات العصبية البني على مر الزمن. المجال ستتم مقارنة النتائج المحمية للشركات والمختبرات والمكاتب الاستثلارية، بالإضافة البني على مر الزمن. المعرب الفرانة النتائج المتحققة من تطبيق هذه الطريقة باستخدام بر مجيات العصبية الإصطناعية "، من خلال جمع قواعد البيانات من التجارب العملية للشركات والمختبرات والمكاتب الاستثمارية، بالإضافة الإصلاعية المحنين في هذا المجال. ستتم مقارنة النتائج المتحققة من تطبيق هذه الطريقة باستخدام بر مجيات العربياة ما ينائج الماحقية باستخدام طريقة العنصر المحدود ، واستخدام من مديور مراي وعربيا وعرب المريون بالإضافة.

كلمات مفتاحية: الرصيف، التدهور، التعزيز، التسليح الاصطناعي الأرضي، الشبكات العصبية الاصطناعية ، طريقة العنصر المحدود ، التنبؤ، قاعدة البيانات، النمذجة، المقارنة.

Abstract

Basic infrastructure, such as roads, engineering structures and airport runways, is considered to be the backbone of any country's transport system and a key factor in economic stability, given the services it provides to meet the needs of the population. Algeria has a very extensive network of roads and runways, most of which are subject to repetitive loads from heavy goods vehicle and aircraft traffic, with dynamic effects. As a result, deterioration and crack propagation can be observed in the wearing courses, leading to a loss of load-bearing capacity in the pavement bodies of these runways, requiring repairs and/or reinforcement as part of routine or ongoing maintenance. The solution of inserting geosynthetic layers has shown very convincing advantages during its application (over the last thirty years). However, there is still little (if any) monitoring of the behaviour of any runway or road reinforced with this type of material. This is why experts and researchers in the field of geotechnics are thinking about finding solutions and predicting the behaviour over time of these infrastructures. This master's thesis proposes a contribution to the understanding of the prediction method known as "Artificial Neural Networks / ANNs", by collecting databases from the practical experience of companies, laboratories and BETs, as well as the

results of researchers in this field. The results obtained from the application of this method using Python programming language will be compared with the results obtained using the finite element method using Ansys/Workbench software. We will then be able to determine the advantages and disadvantages of the two methods, ANNs and FEM, and draw the appropriate lessons.

Key words: Pavement, deterioration, reinforcement, geosyhetics, ANNs, MEF, prediction, database, modeling, comparison

Résumé

Les infrastructures de base, telles que les routes, les ouvrages d'art et les pistes aéroportuaires, se considèrent comme le pivot du transport de tout pays et influent dans la stabilité économique, vu les services qu'elles présentent pour le besoin de la population. L'Algérie dispose d'un patrimoine très important de ce réseau routier et de pistes aéroportuaires et dans la plus part des cas, ce patrimoine est sollicité par des charges répétitives, dues aux trafics des poids lourds et des aéronefs, avec des effets dynamiques. C'est pourquoi, on observe des dégradations et des propagations de fissures sur les couches de roulement, qui donnent lieu à des pertes de capacités portantes des corps de chaussées de ces pistes, ce qui nécessite, des réparations et/ou renforcements, entrant dans le cadre des entretiens courants ou maintenances continues. La solution d'insertion des nappes de géosythétiques, a montré des avantages très convaincants, lors de son application (durant ces trente dernières années). Cependant, le suivi du comportement de toute piste ou route renforcée par ce type de matériau, reste peu (voire rare). C'est pourquoi, les experts et les chercheurs dans le domaine de la géotechnique, songent à trouver des solutions et de prédire le comportement dans le temps de ces infrastructures. Ce mémoire de master, propose une contribution pour la compréhension de méthode prédiction dite "Réseaux de Neurones Artificiels/ ANNs'' et ce, par la collecte de bases de données, issues de l'expérience pratique des entreprises, des laboratoires et BET, ainsi que les résultats des chercheurs dans ce domaine. On comparera les résultats trouvés de l'application de cette méthode par le language "Python" aux résultats trouvés par la méthode des éléments finis à l'aide du logiciel "Ansys/ Workbench". On pourra après, savoir l'avantage et l'inconvénient des deux methodes "ANNs et MEF" et tirer les leçons adéquats.

Mots clés : Chaussée, dégradation, renforcement, géosyhétique, ANNs, MEF, prédiction, base de données, modélisation, comparaison.

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DEDICATIONS

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List of abbreviations

ICBR	Input Current Bias Resistance
N	The number of heavy goods vehicles per
	direction
e	Pavement layer thikness
N1	Lightly travelled road
N2	Busy road
N3	Highly busy road

General Introduction

General Introduction

Over time, a dilemma faced humanity: "Mobility" which is the proper way to facilitate communication, so roads were constructed. The structure of roads is based on elements including pavement, grass sections, ditches and outbuildings.

Pavement is a type of hard surface consisting of a durable surface material laid over an area intended to receive vehicular or pedestrian traffic. Its primary function is to distribute the loads applied by vehicles to the subgrade through different layers. The road surface must provide sufficient skid resistance, good ride quality, favourable light reflection characteristics and low noise pollution. The purpose of the pavement is therefore to reduce the load transmitted by moving loads (vehicles, trucks, bicycles, etc.) so that it does not exceed the load capacity of the subgrade.

Road Pavements are playing a crucial role in the development of any construction. There are mainly two types of road pavement used: flexible and rigid pavements road. Because of heavy goods vehicle traffic with dynamic effects, degradation and propagation of cracks have a significant impact on pavement materials and the underlying subgrade, which in turn can drastically affect pavement performance The solution, consisting of the insertion of geosynthetic layers, has shown very convincing advantages in its application over the last thirty years. This is why experts and researchers in geotechnics are thinking about finding solutions and predicting the behaviour of these infrastructures over time.

As neural networks are part of AI (artificial intelligence), they are best suited for this type of work, thanks to the great robustness of calculations, and a capacity for learning, classification, simulation and prediction. This work aims to predict the behaviour of linear pavements reinforced with geosynthetics, with the addition of the application of artificial neural networks (ANNs).

To carry out this study, this work is divided into six chapters. After a general introduction, the first chapter will focus on the strategy of realization of linear pavements, including their types, repair/reinforcement methods and also the potential degradation of road pavements as well as other techniques.

The second chapter will be devoted to pavement behaviour prediction, analysis and databases, as well as pavement behaviour inspection methods. Finally, in the same chapter, major disasters and their behaviour will be presented. Chapter three will be devoted to understanding neural networks (ANNAs) and their applications in the last twenty years. Similarly, chapter four will be devoted to the collection and processing of databases. Chapter five will contain the application of the ANNAs and the calculation by PYTHON programming language. The last chapter will be devoted to the results and comments and we end with a general conclusion for future research.

CHAPTER I

Linear pavements and their application

LINEAR PAVEMENTS AND THIR APPLICATION

I.1. Strategy for the realization of linear pavements:

I.1.1. Introduction:

Linear pavements are any pavement considered basic infrastructure, requiring a substantial budget and know-how to build. Examples include roads, airport runways and railways, where two dimensions (width and thickness) are negligible compared with the third dimension (length). For the construction of pavement structures, the regulations and the rules of art concerning the manufacture and use of materials must be respected to reassure themselves of the homogeneity of the compositions and the mechanical characteristics. The dimensioning calculation must take into account the fact that the realization is affected by random variations in the thickness of the layers.

I.1.2. Linear pavement:

A linear pavement is a multi-layered structure consisting of three main parts, each of which has a well-defined role [1]. First, the terraced ground or ground support is generally surmounted by a layer of form. The soil-layer-shaped assembly represents the roadway support platform. The shape layer has a dual function. During the works, it ensures the protection of the ground support and allows the quality of the levelling as well as the traffic of the machines. In service, it makes it possible to homogenize the mechanical characteristics of the materials constituting the soil or the fill and improve the long-term lift. Then come the base layer and the foundation layer thus forming the base layers. The seat layers provide the pavement with mechanical resistance to the vertical loads induced by the traffic and distribute the pressures on the support platform to maintain the deformations at an acceptable level

Finally, the surface layer consists of the bearing layer and possibly a bonding layer between the bearing layer and the base layers. It has two functions. On the one hand, it protects the layers of the seat against water infiltration. On the other hand, it gives users a comfortable driving experience that is all the more satisfying when the surface characteristics are good.

I.1.3. Different types of pavements:

Universally, there are different types of pavement, distinguished by the materials making up their pavement body, and their geometric and mechanical characteristics. These include:

- Soft pavements
- Thick bituminous pavements.
- Semi-rigid pavements treated with hydraulic binders.
- Mixed structure pavements.
- Reverse structure pavements.
- Cement concrete pavements.

I.1.4. Phases of pavement construction :

Particular emphasis is placed on the development and construction of roads and road infrastructure. However, the construction of the latter requires months of planning before the actual project is completed. The different phases go through field studies, tracing and finally finishing the work itself. [2]

- Planning and public consultation (6-12 months or more).
- Environmental survey, surveys and preliminary design (1-3 years).
- Plot and land purchase (two years).
- Leveling (from one to two years).
- Works.
- Paving, signage and lighting.

I.2. Types of rigid and flexible pavements:

I.2.1.Introduction:

A pavement is a multilayer structure consisting of three main parts that have each a welldefined role. Pavement types are classified according to their constitution, where each type has properties and specific features.

I.2.2.Rigid Pavements:

Rigid pavement is constructed from cement concrete or reinforced concrete slabs. Grouted concrete roads are in the category of semi-rigid pavements. The design of rigid pavement is based on providing a structural cement concrete slab of sufficient strength to resist the loads

from traffic. The rigid pavement has rigidity and a high modulus of elasticity to distribute the load over a relatively wide area of soil. [3]. Minor variations in subgrade strength have little influence on the structural capacity of a rigid pavement. In the design of rigid pavement, the flexural strength of concrete is the major factor, not the subgrade's strength. Due to this property of pavement, when the subgrade deflects beneath the rigid pavement, the concrete slab can bridge over the localized failures and areas of inadequate support from the subgrade because of slab action (Figure I.1).



Figure I.1: Rigid Pavement Cross-Section [1]

I.2.2.1. Concrete Slab:

The concrete slab is the topmost layer of rigid pavement which is in direct contact with the vehicular loads (Figure I.2). This is also called a surface course. It is water resistant and prevents water infiltration into the base course. It offers friction to the vehicles to provide skid resistance. The thickness of the concrete slab is kept between 150 mm to 300 mm [4].



Figure I.2: Concrete Slab Laying [1]

I.2.2.2.Base Course:

The base course or granular base or stabilized base is the second layer from the top and is constructed using crushed aggregates. This course helps the surface course to take additional loads. It provides a stable platform to construct rigid pavement It is also useful to provide a subsurface drainage system. In frost areas, the frost action can be controlled by the stabilized base course. It helps to control the swelling of subgrade soil. The base course thickness should be a minimum of 100mm [4].



Figure I.3: Providing Base Course [1]

I.2.2.3. Subbase :

Granular Subbase or Stabilized Subbase Course is the third layer from the top and is in contact with the subgrade soil and base course. It is constructed by using low-quality aggregates than the base course but they should be better quality than subgrade. Generally, a subbase course is not required when the traffic loading is light. When the loading exceeds 100000 pounds it should be constructed. Its primary function is to provide support for the top layers and it also serves as a frost action controller and prevents the intrusion of fines from the subgrade to the top layers. The drainage facility will also improve when there is a subbase course.



Figure I.4: Laying of Subbase Course [1]

I.2.2.4. Subgrade:

The subgrade is nothing but the existing soil layer which is compacted using equipment to provide a stable platform for rigid pavement. The subgrade soils are subjected to lower stresses than the top layers since the stresses will reduce with depth. Subgrade soils may vary considerably. The stresses coming from the top layers are received by different soils in different manners. Some soils may resist them and some may not. It depends upon the interrelationship of texture, density, moisture content and strength of subgrade. So, a proper examination should be done on the subgrade before construction. At the same time, the pavement layers above the subgrade should be capable of reducing stresses imposed on the subgrade soil to prevent the displacement of subgrade soil layers.



Figure I.5: Preparing Subgrade Soil [1]

I.2.3. Flexible pavements:

Flexible pavement can be defined as one consisting of a mixture of asphaltic or bituminous material and aggregates placed on a bed of compacted granular material of appropriate quality in layers over the subgrade. Water-bound macadam roads and stabilized soil roads with or without asphaltic toppings are examples of flexible pavements. The design of flexible pavement is based on the principle that for a load of any magnitude, the intensity of a load diminishes as the load is transmitted downwards from the surface by spreading over an increasingly larger area, by carrying it deep enough into the ground through successive layers of granular material [5]. Thus for flexible pavement, there can be grading in the quality of materials used, the materials with a high degree of strength are used at or near the surface. Thus the strength of the subgrade primarily influences the thickness of the flexible pavement.



Figure I.6: Flexible Pavement Cross-section [1]

I.2.3.1. Surface course:

The surface course or wearing course is the topmost layer of flexible pavement which has direct contact with the vehicular loads. Since it is directly in contact with traffic, good quality aggregates and highly dense bitumen or asphalt are recommended for the construction of the surface course. The main function of the surface course is to provide skid-resistance surface, friction and drainage for the pavement. It should be watertight against surface water infiltration. The thickness of the surface course generally provided is 25 to 50 mm [5].



Figure I.7: Surface Course [1]

I.2.3.2. Base Course:

The base course is an important layer of pavement structure and it distributes the loads from the top layers to the underneath Subbase and sub-grade layers. It provides structural support for the pavement surface. It is constructed with hard and durable aggregates which may either be stabilized or granular or both. The thickness of the base course must be great enough to reduce the load capacity on sub-grade and Subbase courses. The minimum base course thickness recommended is 100 mm. subsurface drainage system can be provided within the base course [5].



Figure I.8: Laying Base Course [1]

I.2.3.3. Subbase Course:

The Sub-base course is provided beneath the base course and it also functions as same as the base course. If the sub-grade soil is strong and stiff, then there is no need to sub-base course.

Granular aggregates are used to construct a sub-base course. If the subgrade is a weak minimum of 100 mm thick sub-base course should be provided [5].



Figure I. 9: Laying Sub-base course [1]

I.2.3.4. Subgrade:

The subgrade is the bottom-most layer which is nothing but natural soil layer compacted up to the required depth generally about 150 to 300 mm to receive the loads coming from the top layers. This layer is termed the foundation of the pavement system. The sub-grade should be strong enough to take the stresses and also it is important to keep the stresses coming from top layers should be within the limit of sub-grade capacity. To reduce the amount of stress on soil subgrade, provide thick layers of base course, Sub-base course and surface course.



Figure I.10: Compacting Sub-grade [1]

Apart from the above layers, three types of coats or finishes are provided in the flexible pavement system which are as follows: seal coat, tack coat and prime coat.

I.3.Degradation of potential road pavements and Aero:

I.3.1.Preamble:

In public works, linear pavements are used for roads, motorways, airport runways and car parks, and are subject to excessive traffic loads and extreme weather conditions. The various types of these pavements are designed to have a high structural capacity to withstand heavy loads to avoid ongoing maintenance in the face of cracking, local spalling and other deterioration. These pavements may have surface cracks due to tensile stresses from repeated moving loads or even climatic effects, and these cracks may propagate downwards and affect the lower layers, significantly reducing the structural capacity of the pavement and increasing the risk of damage [6, 7]. The growth of heavy traffic, vehicle overloads and climate stress are degrading pavement structures.

There are two types of degradation:

Structural degradation: occurs within the structure of the road or its support.

Superficial degradation: have its origin in the surface layer of the pavement and first affects its surface qualities (safety and comfort in particular). [6]

I.3.2.Cracks:

Several different types of cracks can develop in asphalt pavements. The repair depends on the type of crack. Some cracks are load-related and some are attributable to temperature or environment.

• Fatigue Cracking:

Fatigue cracking is sometimes called alligator cracking due to the interconnected cracks which resemble alligator skin. Fatigue cracking is caused by load-related deterioration resulting from a weakened base course or subgrade, too little pavement thickness, overloading, or a combination of these factors.



Figure I.11: Fatigue Cracking [1]

Block Cracking:

Block cracking is a series of large (typically one foot or more), rectangular cracks on an asphalt pavement surface. This type of cracking typically covers large areas and may occur in areas where there is no traffic. Block cracking is typically caused by shrinkage of the asphalt pavement due to temperature cycles.



Figure I.12: Block Cracking [1]

• Edge Cracking:

Edge cracks are longitudinal cracks which develop within one or two feet of the outer edge of a pavement. These cracks form because of a lack of support at the pavement edge.



Figure I.13: Edge Cracking [1]

• Longitudinal Cracking:

Longitudinal cracks occur parallel to the centerline of the pavement. They can be caused by: a poorly constructed joint; shrinkage of the asphalt layer; cracks reflecting up from an underlying layer; and longitudinal segregation due to improper paver operation. These cracks are not load-related.



Figure I.14: Longitudinal Cracking [1]

• Transverse Cracking:

Transverse cracks occur roughly perpendicular to the centerline of the pavement. They can

be caused by shrinkage of the asphalt layer or reflection from an existing crack. They are not load-related.



Figure I.15: Transverse Cracking [1]

• Reflection Cracking:

Reflection cracks are cracks that form over joints or cracks in concrete pavement or in an overlay of deteriorated asphalt pavement. The cracks form because of the movement of the old pavement.



Figure I.16: Reflection Cracking [1]

• Slippage Cracking:

Slippage cracks are crescent-shaped cracks which form because of low-strength asphalt mix or a poor bond between pavement layers. The cracks form due to the forces applied by the turning or braking motion of vehicles.



Figure I.17: Slippage Cracking [1]

I.3.3.Distortion:

Distortions in asphalt pavement are caused by the instability of an asphalt mix or the weakness of the base or subgrade layers. This distress may include rutting, shoving, depressions, swelling and patch failures.

• Rutting:

Rutting is a linear, surface depression in the wheel path. Rutting is caused by the deformation or consolidation of any of the pavement layers or subgrade. It can be caused by insufficient pavement thickness, lack of compaction, and weak asphalt mixtures.



Figure I.18: Rutting [5]

• Shoving:

Shoving is the formation of ripples across a pavement. This characteristic shape is why this type of distress is sometimes called wash-boarding. Shoving occurs at locations having severe horizontal stresses, such as intersections. It is typically caused by: excess

asphalt; too much fine aggregate; rounded aggregate; too soft an asphalt; or a weak granular base.



Figure I.19: Shoving [5]

• Depressions:

Depressions, also call bird baths, are localized low spots in the pavement surface. These flaws can be caused by settlement or another failure in the lower pavement layers or by poor construction techniques.



Figure I.20: Depressions [5]

• Upheaval:

Upheaval is a localized upward movement in the pavement due to swelling of the subgrade.



Figure I.21: Upheaval [5]

• Patch Failures:

When pavements are patched, some distress may begin to occur. The rate at which a patch deteriorates is influenced by compaction, materials selection, and the quality of the surrounding or underlying pavement.



Figure I.22: Patch Failures [5]

I.3.4.Disintegration:

Disintegration is the breakup of a pavement into small pieces that are lost with time and traffic. Ravelling and potholes are the most common types of disintegration.

• Raveling:

Ravelling is the wearing away of the aggregate particles from the asphalt cement. This condition indicates that the asphalt has hardened or that a poor-quality mixture was used. Ravelling occurs in the presence of traffic.



Figure I.23: Raveling [5]

• Potholes:

Potholes are bowl-shaped holes caused by the localized disintegration of the pavement surface. Potholes typically result from the continued deterioration of another type of distress. Segregation, cracks or failed patches may serve as the start of a pothole. Poor mixtures and weak spots in the base or subgrade accelerate pothole failures.



Figure I.24: Potholes [5]

I.3.5.Skidding Hazards:

Skidding hazards are caused by water on the surface of the pavement, polished aggregates, or excess asphalt or other lubricants on the pavement surface. Maintaining a pavement which allows water to flow off the pavement is a basic consideration.

• Polished Aggregate:

Some aggregates are susceptible to wearing to a smooth finish or texture under traffic. These aggregates should not be used in wearing courses. If the aggregate polishes, the surface roughness must be restored.



Figure I.25: Polished Aggregate [5]

• Bleeding:

A pavement surface can become flushed with asphalt and lose its skid resistance. Bleeding can be caused by too much asphalt in the mix, excess tack or bond coat, or by poor construction of a seal coat. Traffic can also over-compact an unstable mix and force asphalt to the surface.



Figure I.27: Bleeding [5]

I.3.6.Surface Treatment Distress:

Surface treatments can experience their own distresses. These include loss of cover aggregate and streaking.

• Loss of Cover Aggregate :

Surface treatments can lose the aggregate cover prematurely. Typically this is caused by: spreading the chips too late in the construction process; using a dirty aggregate;

allowing traffic to use the surface before the aggregate is seated and bonded; or applying too little asphalt to embed the aggregate.



Figure I.28: Loss of Cover Aggregate [5]

• Streaking:

Streaking is the presence of alternating stripes of aggregate or asphalt. Streaking is primarily caused by the uneven application of the asphalt to the pavement surface before the aggregate chips are applied.



Figure I.29: Streaking [5]

I.4.Linear pavement repair/reinforcement methods:

I.4.1. Preamble:

Linear pavement repair and reinforcement methods are an important part of maintaining a roadway. These methods are used to repair small to large sections of pavement that have

been damaged by cracks, potholes, and other surface problems. Various materials and processes can be used to repair and reinforce pavement, such as adding asphalt, sealing coating, and applying a surface treatment. The type of process used depends on the severity of the damage and the desired outcome for the repair. In addition to the traditional techniques based on the application of asphalt concrete layer as an overlay or the application of modified bitumen (MB) layers, or even high modulus asphalt concrete (HMAC), can significantly improve the mechanical properties of the pavement.

I.4.2. Linear pavement repair/reinforcement methods:

I.4.2.1. Sealcoating:

An important part of maintaining a driveway or parking lot. The process involves applying a sealant to the surface of the asphalt, which helps protect it from the elements and extends its lifespan. Sealcoating also improves the appearance of the asphalt. It helps restore the original black colour, making it look newer and more attractive [7].



Figure I.30: Sealcoating [2]

I.4.2.2. Geosynthetics:

Geosynthetics have been successfully used to fulfil several functions that contribute significantly to the good performance of roadways. They include the functions of separation, filtration, reinforcement, stiffening, drainage, barrier, and protection. The applications include the migration of reflective cracking in asphalt overlays, separation, stabilization of road bases, stabilization of road soft subgrades, and lateral drainage [8].


Figure I.31: Application of geosynthetic in the road repair [2]

I.4.2.3. Full-Depth Reclamation (FDR):

FDR is an in-place recycling method for the reconstruction of existing flexible pavements using the existing pavement section material as the base for the new roadway-wearing surface. This process can include adding chemicals to the base layer to increase its strength capacity. The treatment of the base layer and recycled asphalt provides a stronger foundation for present and future traffic [9].



Figure I.32: Full-Depth Reclamation [2]

I.4.2.4. Fiber matrix systems:

This system consists of a set of fibres that are interconnected to create a web-like structure. Each fibre is connected to the others, forming a continuous matrix. The benefits of the system are that it is capable of providing uniform coverage with minimal gaps, while also being easy to install and maintain. [10]

I.4.2.5. Thin-lift asphalt overlay :

It is an effective way of repairing asphalt sections that are beginning to degrade. The process involves the application of a thin layer of asphalt over the existing pavement structure. The thin-lift overlay is designed to be flexible and provide a water-resistant and durable surface to the pavement. [11]



Figure I.33: Thin-lift asphalt overlay [2]

I.4.2.6. Dowel Bar Retrofit (DBR):

Dowel bar retrofit involves the installation of dowel bars through existing transverse joints in concrete pavements to improve load transfer capacity and reduce faulting. This method can be used to extend the life of joint concrete pavements and reduce maintenance costs. [12]



Figure I.34: Dowel Bar Retrofit [2]

I.4.3.Conclusion:

Linear pavement reinforcement methods have been increasingly used in the last decade as an effective way to extend the life of pavement structures. The goal of all linear pavement reinforcement methods is to restore the structural integrity of pavements and prevent further deterioration. Linear pavement reinforcement methods have emerged as a valuable strategy for preserving and enhancing the performance of pavement structures. Through techniques the structural integrity of pavements can be restored, leading to increased durability and reduced maintenance costs. By incorporating the methods into pavement rehabilitation plans, transportation agencies can effectively address the challenges posed by an ageing infrastructure and ensure the longevity and sustainability of our road networks.

I.5.New technology:

Highway planning agencies have constructed some of the best roads in the world with the help of technological systems, software, and equipment. With advanced tools, large stretches of roads can be constructed or improved in minimal time. And by efficiently improving road networks, organizations can tackle road safety and traffic flow, reducing congestion and limiting the risks of collisions. So here are five technologies that have improved road construction, and brought us some of the most efficient highways. [13]

I.5.1.LiDAR Systems:

Before roads can be improved or constructed, transport agencies carry out surveys of existing roads, infrastructure, and land for potential new routes. The information gathered in these surveys can help teams analyze the condition and layout of roads and plan new routes or reconstructions. In the past, organizations used traditional surveying methods and equipment such as theodolites to collect information from roads. However, modern surveys now use LiDAR, also known as light detection and ranging technology. These systems collect detailed information from the Earth's surface using laser light pulses to gather 3D coordinates from the scanned area. LiDAR systems collect millions of coordinates or "points" in a survey, which together form a "point cloud."

Point clouds, when analyzed with the right software, form a detailed and accurate digital representation of the surveyed environment — a 3D CAD model. This model can be used

by highway planning agencies to inspect existing roads and routes, analyze the condition of surfaces and identify and locate features such as sidewalks, signs, and guard rails. This information can then help organizations make informed decisions regarding highway planning projects. [13]



Figure I.35: LiDAR Systems . [2]

I.5.2.Point Cloud Processing and Computer Modelling Software :

This technology goes hand in hand with LiDAR. Point cloud processing software transforms millions of coordinates gathered in LiDAR surveys into a 3D digital model of the surveyed area. Teams and individual contractors can then use the CAD model to inspect land, roads, and infrastructure. The layout of roads and junctions can be reviewed and even tested using vehicle simulation. By moving a digital vehicle through the CAD model, teams can identify and locate collision risks and traffic flow issues. This software can also simulate new road construction, so new routes, as well as existing ones, can be tested and analyzed. By carrying out analysis in the safety of the digital world, agencies can identify potential issues before road works begin. This way, road construction projects are more likely to be successful, cost-efficient, and timely. [13]

I.5.3.Drones:

Another type of technology used by highway planning agencies all over the world is UAVs. Drones have become vital tools for road surveying teams as they can be mounted with LiDAR systems and used to survey vast areas of land in a short space of time. By surveying from the skies, organizations can produce digital terrain maps of large areas, which are used by highway planning agencies and can also contribute to mapping and navigation. [13]



Figure I.36: Drones [2]

I.5.4.Anti-Icing Road Surface Technology :

In colder destinations, ice can pose a serious safety risk on roads, causing drivers to lose control of their vehicles. But scientists have developed a technology designed to limit the risk of winter driving: road surfaces that can de-ice themselves. These surfaces are being used by highway planning agencies around the world, from Europe to the USA [13]. These surfaces are made with a salt potassium formula and gradually release de-icing salt. Not only does this make roads safer for drivers, but it also saves councils money on de-icing road-clearing efforts.

Electric cars are growing in popularity every day, so it makes sense that transport agencies are building roads with electric vehicles in mind. But one issue with these cars is range. While electric vehicles can now go much further on a single charge than they could previously, battery range can still be an issue for those travelling long distances. So, scientists have developed roads that can charge cars as they drive. Electric rails or embedded magnetic fields are laid beneath road surfaces and energy transfers to the vehicle via a coil inside the car. This energy then charges the car's battery. These roads are completely safe to walk on, even in the rain, so there's no safety risk to pedestrians. Dynamic charging, Electric Priority Lanes have been tested in the UK, and the very first electrified road opened in Sweden in 2018. This dynamic charging technology is likely to be adopted by more transport agencies in the future, improving roads for electric vehicle drivers.

CHAPTER II

Prediction of pavement behaviour

Prediction of pavement behaviour

II.1. Behavior of linear pavements:

II.1.1 Genesis and Literature:

Roads and airport runways are subjected to cyclical and sometimes excessive loads during their use. In addition, the stresses caused by harsh environmental conditions lead to a loss of pavement structural characteristics. Although owners regularly inspect runways and taxiways and carry out routine maintenance and/or emergency repairs, it is always necessary to find appropriate solutions to guarantee the safety of these infrastructures and restore their original mechanical properties. The solution generally depends on the type of degradation, crack propagation and material fatigue [10]. Several strengthening techniques have been applied in flexible pavements in road and runway repairs during the last twenty years. In addition to the traditional technique based on the application of a bituminous concrete layer, the application of modified bitumen and high modulus can significantly improve the mechanical properties of pavements that have lost part of their mechanical characteristics, the application of geosynthetics systems become an alternative efficient repair solution [11, 12].

The most widespread geosynthetic materials for this type of application are geogrids. The performance of geogrids depends on the constituent material of the grid, the shape of the mesh, the dimensions, the rigidity and the position in the section. Geogrids increase the fatigue resistance, reduce degradation over time, reduce crack propagation and increase structural performance. Recent research work highlighted the influence of these parameters through laboratory and situ investigations by non-destructive testing, especially on roads. Indeed, the position of the geogrid in the flexible pavement structure is one of the most widely discussed subjects over the past three decades due to the important effects it produces during its use on roads [13]. The influence of geogrid on energy absorption and on reducing crack propagation has been investigated [14], [15]. Austin and Gilchrist [16] tried to optimize the strengthening of bituminous concrete pavement using flexible biaxial geogrid behaviour of the surface layer reinforced with geogrid was evaluated experimentally [17]. The effect of the bond between the asphalt and the geogrid on pavement behaviour and the optimization of the thickness of sub-layer- were also studied [18].

For road design, maintenance and repair, prediction of pavement behaviour is essential. Pavement design can be improved, maintenance costs can be reduced and the life of the pavement can be increased thanks to accurate predictions of its behaviour.

II.1.2. Techniques for the prediction of pavement behaviour:

Techniques for the prediction of pavement behaviour play a crucial role in the field of transportation engineering and infrastructure development. These techniques enable engineers to assess and forecast the performance of pavements under various loading and environmental conditions.

By accurately predicting the behaviour of pavements, engineers can make informed decisions regarding design, construction, and maintenance strategies, ultimately ensuring safer and more durable roadways. One of the primary objectives of pavement behaviour prediction is to estimate the response of the pavement structure to the applied loads, including traffic loads from vehicles, environmental factors such as temperature and moisture variations, and other external forces. This prediction involves understanding how the pavement materials, including asphalt, concrete, and granular layers, will deform and interact under these conditions. In conclusion, it can be said that the ability to study pavement conditions by calculation, detection or modelling, and to predict them accurately, is essential to the success of pavement management systems [19].

Various techniques and methodologies have been developed to achieve reliable pavement behavior prediction such as:

II.1.2.1. Empirical approaches:

Empirical approaches are founded on statistical correlations between pavement performance and characteristics related to the environment, traffic, and materials. These techniques create regression models based on previous data to forecast pavement performance over time. Empirical approaches' key benefits are their affordability and ease of use [14]. They can't take into account changes in the weather, traffic, or material circumstances, and their accuracy is limited.

II.1.2.2. Mechanistic-empirical (ME) models:

Mechanistic-empirical models predict pavement performance by fusing theoretical and empirical models. These models simulate the structural response of the pavement system to environmental and traffic loads using physical principles and empirical data. ME models are better able to predict pavement performance because they can make changes in the environment, traffic, and material conditions into account. They are more complicated than empirical models though, and they also need more information and resources [15].

II.1.2.3. Finite element analysis (FEA):

FEA is a numerical modelling technique that simulates the structural behaviour of the pavement system using sophisticated mathematical algorithms. FEA can analyze the stress and strain distribution within the pavement layers in great detail and can take into account geometric and material nonlinearities. Although FEA is very accurate, developing and validating the models requires significant computational resources and expertise. [16]

II.1.2.4. Artificial Intelligence and Machine Learning:

AI and ML techniques use large datasets to train models that can recognize patterns and make predictions. By feeding the models with input variables such as traffic data, climate data, and pavement characteristics, they can learn to forecast pavement performance and deterioration trends. [17]

II.1.2.5. Accelerated Pavement Testing (APT:)

APT involves subjecting pavement sections to accelerated loading in a controlled environment to simulate long-term traffic and environmental effects in a shorter time frame. By monitoring the performance of the pavement during the testing period, engineers can predict how the pavement will behave under real-world conditions. APT provides valuable data for model calibration and validation. [18]

II.1.2.6. Pavement Response Modeling :

This technique involves developing mathematical models to predict the response of pavements to external loads and environmental conditions. These models incorporate material properties, structural configuration, and boundary conditions to estimate pavement stresses, strains, and deformations. [19]

II.1.2.7. Geographic Information Systems (GIS):

GIS technology integrates spatial data with pavement attributes and performance data to analyze and predict pavement behaviour. It enables the identification of critical locations, prioritization of maintenance activities, and assessment of environmental impacts. [20]

II.1.2.8. Pavement Design Catalogs:

Pavement design catalogues provide guidelines and standardized procedures for pavement design based on anticipated performance. Thescataloguesgs consider various factors like traffic volumes, axle loads, climate, and material properties to predict the behaviour and performance of different pavement designs.

II.1.2.9. Expert Systems:

Expert systems are computer-based programs that utilize expert knowledge and rules to make predictions or provide recommendations. In the context of pavement behaviour prediction, expert systems can incorporate engineering expertise to assess pavement conditions, evaluate distresses, and predict future performance.

II.1.2.10. Artificial Neural Networks (ANN):

ANN is a computational model inspired by the human brain's neural networks. In pavement behaviour prediction, ANN models can learn patterns and relationships from input data and make predictions based on the learned knowledge. They are useful for capturing complex interactions between variables. [21]

II.1.2.11. Genetic Algorithms (GA) :

GA is an optimization technique based on the principles of natural selection and genetics. In pavement behaviour prediction, GA can be used to search for optimal solutions by iteratively refining a set of input parameters to improve the accuracy of predictions and model calibration.

II.1.2.12. Markov Chains:

Markov Chains are mathematical models that analyze a sequence of events or states where the future state depends only on the current state. In pavement behaviour prediction, Markov Chains are used to predict the future behaviour of systems by estimating transition probabilities between states based on historical data. In the context of pavement behaviour prediction, Markov Chains analyze the deterioration or condition transitions of pavements over time to assist in maintenance planning and resource allocation.

II.1.2.13. Back calculation:

The back calculation is a technique used to determine the material properties of pavement layers by analyzing field data such as falling weight deflectometer (FWD) measurements. It estimates the material properties (layer thicknesses, moduli, and strengths) by analyzing the deflection response of the pavement under a known load. These properties are used in predictive models.

II.1.2.14. Climate Change Modeling:

Climate Change Modeling refers to the use of mathematical and computational models to forecast the impact of climate change on pavement performance. These techniques integrate climate projections, including temperature and precipitation changes, with pavement behaviour models to assess potential deterioration, structural integrity, and maintenance requirements under future climate scenarios. Climate Change Modeling helps engineers and planners make informed decisions regarding pavement design, materials selection, and adaptation strategies to ensure the resilience and sustainability of road infrastructure in the face of changing climatic conditions. [22]

II.1.2.15. Pavement Management Systems (PMS) :

PMS refers to integrated software systems that assist in the evaluation, planning, and management of pavement assets. PMS utilize data on pavement condition, traffic volumes, and other factors to assess the current and future performance of road networks. These systems incorporate predictive models, deterioration models, and optimization algorithms to forecast pavement behaviour, prioritize maintenance and rehabilitation activities, and allocate resources effectively. PMS provide decision support tools for pavement managers to ensure cost-effective and sustainable maintenance strategies while considering budget constraints and performance targets.

II.1.2.15. 3D Laser Scanning:

3D laser scanning involves using laser technology to capture high-resolution threedimensional images of pavement surfaces. These scans provide detailed information about surface roughness, texture, and distress, allowing for the accurate evaluation of pavement conditions and predicting the progression of distress over time.

II.1.3. Artificial Intelligence and machine learning techniques :

Pavement engineering is increasingly using artificial intelligence (AI) and machine learning (ML) techniques to forecast pavement performance. Large data sets can be used by AI and ML to build predictive models that can spot patterns, connections, and trends that humans might not notice right away. [23]

II.1.3.1. Convolutional Neural Networks (CNNs) :

CNNs are a type of neural network that can analyze and learn from images. In pavement behaviour prediction, CNNs can be used to analyze pavement images captured by cameras or drones to detect and classify different types of pavement distress.

II.1.3.2. Recurrent Neural Networks (RNNs):

RNNs are a type of neural network that can analyze sequential data, such as time series data. In pavement behaviour prediction, RNNs can be used to analyze pavement performance data collected over time, such as rutting, cracking, and roughness, to predict future pavement behaviour.

II.1.3.3. Support Vector Machines (SVMs) :

SVMs are a type of machine learning algorithm that can analyze data and classify it into different categories. In pavement behaviour prediction, SVMs can be used to analyze various factors that affect pavement performance, such as traffic volume, weather, and pavement type, to predict pavement behaviour.

II.1.3.4. Decision Trees :

Decision trees are a type of machine learning algorithm that can analyze data and make predictions based on a set of rules. In pavement behaviour prediction, decision trees can be used to analyze various factors that affect pavement performance, such as pavement type, climate, and traffic, to predict pavement behaviour.

II.1.3.5. Bayesian Networks:

Bayesian networks are a type of probabilistic graphical model that can be used to analyze complex systems. In pavement behaviour prediction, Bayesian networks can be used to

analyze various factors that affect pavement performance, such as pavement type, climate, and traffic-predicted pavement behaviour.

II.1.3.6. Deep Learning:

Deep learning is a subset of AI that uses deep neural networks to analyze and learn from data. In pavement behaviour prediction, deep learning can be used to analyze large datasets of pavement performance data to predict future pavement behaviour.

II.1.4. Performance models for specific pavement types:

To forecast how a pavement structure will behave over time, performance models are used. These models frequently combine empirical data with mechanistic analysis and/or finite element analysis. For various pavement types, including rigid and flexible pavements, specific performance models have been developed.

II.1.4.1. Performance models for rigid pavements :

Performance models are used to predict the behaviour and performance of concrete pavements over time for rigid pavements. These models are typically based on a mechanistic-empirical approach, which means they take into account both the performance data that has been observed and the underlying physics of the pavement structure. [24]

The following significant variables and elements are frequently taken into account in performance models for rigid pavements :

- Concrete's physical characteristics, such as its durability, stiffness, and strength.
- Subgrade support is the term used to describe a soil's capacity to support the weight of a pavement structure.
- Traffic loads are frequently defined by the quantity and mass of the vehicles that will be driving on the pavement.
- environmental elements like humidity, temperature, and freeze-thaw cycles.
- Features of the pavement design, like joint spacing and slab thickness.

Depending on the specific requirements of the project and the data at hand, performance models for rigid pavements can take many different shapes. Several popular models include.

• Empirical models, which are founded on statistical correlations between observed pavement performance and the influencing variables.

- Mechanistic models, which describe how the pavement structure behaves under various loading and environmental conditions using mathematical equations.
- Mechanistic-empirical models, which bring together the best features of both empirical and mechanistic models, can predict pavement performance more precisely and comprehensively.

II.1.4.2. Performance models for flexible pavements :

Performance models are used to predict the behaviour and performance of asphalt pavements over time for flexible pavements. These models typically employ a mechanistic-empirical methodology that takes into account both the performance data that has been measured and the underlying physics of the pavement structure. [25]

The following significant variables and elements are frequently taken into account in performance models for flexible pavements:

- Asphalt's physical characteristics, such as its stiffness, resistance to fatigue, and resistance to permanent deformation.
- Subgrade support is the term used to describe a soil's capacity to support the weight of a pavement structure.
- The traffic of the vehicles using the pavement together make up traffic loads.
- Environmental elements like humidity, temperature, and freeze-thaw cycles.
- Features of the base and sub-base layers and the thickness of the asphalt layers in the pavement.

Depending on the specific requirements of the project and the data at hand, performance models for flexible pavements can take many different shapes. Several popular models include :

- Empirical models, which are founded on statistical correlations between observed pavement performance and the influencing variables.
- Mechanistic models, which describe how the pavement structure behaves under various loading and environmental conditions using mathematical equations.
- Mechanistic-empirical models, which bring together the best features of both empirical and mechanistic models, can predict pavement performance more precisely and comprehensively.

II.2. Inspection method of pavement behaviour:

II.2.1. Pavement Inspection:

Pavement inspection is a crucial aspect of maintaining roadways and ensuring the safety of drivers. It involves the assessment of pavement conditions, identifying any defects or damage and determining the best course of action for repair or maintenance. There are various methods of pavement inspection, including visual inspections, non-destructive testing, and laboratory analysis. Each method has its advantages and limitations, and the choice of method depends on the project's specific needs. A combination of visual inspection, manual distress surveys, and non-destructive testing methods can provide a comprehensive evaluation of the behaviour of pavements. These inspection methods are essential for maintaining safe and efficient roadways and can help identify maintenance needs and prioritize repair and rehabilitation efforts. [26]

II.2.1.1 Visual Inspection:

Visual inspection is one of the most common methods used to evaluate the condition of pavement surfaces. This technique involves walking or driving along the pavement and looking for signs of distress such as cracks, potholes, rutting, and other types of damage. To enhance the accuracy of visual inspections, specialized equipment such as high-resolution cameras, drones, and laser scanners can be used to capture detailed images of the pavement surface. These images can then be analyzed using computer software to identify and quantify various types of distresses.

II .2.1.2. Non-Destructive Testing:

Non-destructive testing (NDT) is a method of pavement inspection that uses specialized equipment to evaluate the condition of the pavement without causing damage. NDT methods include ground-penetrating radar, seismic testing, and infrared thermography.

NDT is particularly useful for identifying subsurface defects and assessing the pavement's structural integrity. It can also provide information on the thickness and composition of the pavement layers.

II .2.1.3. Laboratory Analysis Method:

Laboratory analysis involves collecting samples of the pavement and analyzing them in a laboratory to determine their properties and composition. This method is particularly useful for assessing the quality of materials used in pavement construction and identifying potential issues with the mix design.

Laboratory analysis can also provide information on the durability and expected lifespan of the pavement, as well as the best course of action for repair or maintenance.

II .2.2. Data Analysis and Interpretation:

Once the inspection and testing data has been collected, it must be analyzed and interpreted to develop an accurate assessment of the pavement condition. This involves identifying the types and severity of distress, determining the causes of any defects or deterioration, and evaluating the overall structural integrity of the pavement.

The results of the data analysis are then used to develop maintenance and rehabilitation strategies that can help address any identified issues and extend the service life of the pavement. These strategies may include crack sealing, pothole patching, overlay or reconstruction of the pavement layers, or other types of repair or maintenance activities.

II .2.3. Benefits of Pavement Inspection:

Regular pavement inspection is essential for maintaining road safety and reducing the risk of accidents. It can also help to identify potential issues early on before they become more significant problems.

By identifying defects and damage early on, pavement inspection can help reduce repair costs and extend the pavement's lifespan. It can also help to ensure that the pavement meets regulatory standards and requirements.

II .2.4. Automated distress surveys:

which involves using cameras and lasers to collect data on pavement distress. These methods can provide more detailed and accurate data, but they are also more expensive and require specialized equipment.

II.3. Major Catastrophes and Behavior:

Major catastrophes like earthquakes, floods, landslides, and storms can significantly alter the behaviour of pavement. These incidents load to lengthy travel times, expensive repair expenses, or even fatalities.

It is crucial to take into account these significant disasters and their potential consequences on roadways when projecting pavement behaviour. The many disasters kinds and their unique effects on pavements must be taken into consideration when developing methods for predicting pavement behaviour. For instance, in the event of an earthquake, roadways may sustain damage as a result of pavement damage, ground liquefaction, or pavement subsidence. The behaviour of pavements during an earthquake must be predicted using predictive models, which must be able to consider these possible consequences. Similar to how erosion, cracked pavement, and underwater flooding can harm pavements during floods or storms. The behaviour of pavements during a flood or storm must be predicted by predictive models, which must be able to consider these potential consequences.

Ultimately, predicting pavement behaviour requires considering several variables, such as the surrounding environment, the construction's calibre, and the road's expected use. It is possible to better anticipate how pavements will behave in challenging scenarios and devise ways to reduce damage and disturbance by integrating the effects of significant catastrophes in these prediction models.

II.4. Emerging materials and technologies for improving pavement performance and durability:

The performance and durability of pavement constructions are continuously being improved through the development and testing of new materials and technologies. These components and methods can aid in lowering maintenance expenses, enhancing safety, and extending the useful life of pavements. Emerging materials and technology examples include [27] :

• Warm-mix asphalt: Unlike conventional hot-mix asphalt, this form of asphalt may be made and used at lower temperatures. This may lead to decreased energy use, fewer pollutants, and better usability.

- High-performance concrete is a type of concrete that, when compared to conventional concrete, has greater strength, durability, and crack resistance. It can be used in high-thigh and durability applications, such as hard pavements.
- High-performance concrete is a type of concrete that, when compared to conventional concrete, has greater strength, durability, and crack resistance. It can be used in high-thigh and durability applications, such as hard pavements.
- Concrete that has been reinforced with tiny fibres—usually composed of steel, glass, or synthetic materials—to increase its durability and resistance to breaking. Both stiff and flexible pavements can use it.
- Concrete and asphalt pavements that have pores allow water to pass through them and into the soil beneath. They can lessen noise, increase skid resistance, and help to improve water quality by reducing stormwater runoff.
- Recycled components: Recycled components, such as reclaimed asphalt pavement (RAP) and recycled concrete aggregate (RCA), can be utilized in the construction of new pavement to lessen the demand for virgin components and increase sustainability.
- Advanced sensors and monitoring tools can be used to track the performance of pavement in real-time, identifying issues and providing solutions before they worsen.
 Strain gauges, accelerometers, and pavement temperature sensors are a few examples.

These new materials and technologies provide several important advantages, such as enhanced performance, lower maintenance costs, better sustainability, and enhanced safety.

But there are also difficulties with their application, including :

- Higher up-front costs.
- Potential compatibility problems.
- The requirement for specialized tools and training.

CHAPTER III

Neural networks

NEURAL NETWORKS

III.1. Definitions and background:

Neural networks are a set of algorithms modelled after the human brain that can recognize patterns and learn from data. They have become increasingly popular in recent years due to their ability to solve complex problems in various fields such as image recognition, natural language processing, and robotics. The basic building block of a neural network is a neuron, which receives input signals, processes them, and generates an output signal (Figure III.1). The neurons are connected in layers, with each layer performing a specific function in the overall computation.

The first journal article on neural network application in civil/structural engineering was published by **Computer-Aided Civil and Infrastructure Engineering** in 1989. This article reviews neural network articles published in archival research journals since then [20]



Figure III.1: Neural network architecture [20]

III.2. The biological neuron:

It seems useful to give some definitions of the technical terms used [28]:

- The cell body: also called soma. It contains a nucleus surrounded by the structures and corpuscles necessary for its metabolism.
- Axon: axon is the main cell extension. It is through the axon that the neuron will transmit information. At its end is the terminal arborization (transmitter pole of the cell) at the end of which there is a more or less important number of synaptic terminations.
- Dendrites: Dendrites are the second type of cell extension and are found in large quantities around soma, which is why we often speak of dendritic arborization.
 Dendrites are the cell's pole receptor and this is where the connections with other neurons will be made.
- Synapse: It is a junction between two neurons generally (because there are axoaxonal synapses for example) between the axon of a neuron and a dendrite of another neuron.



Figure III.2: Biological neuron [21]

III.2.1. Formal neuron :

The following figure shows how to go from a biological neuron to a formal neuron. Each element of the biological neuron is assimilated into the formal neuron [28].



Figure III.3: The transition from biological neuron to formal neuron [21]

A formal neuron is a non-linear, bounded algebraic function, the value of which depends on the following parameters

- Inputs (Xi): directly system inputs or can come from other neurons.
- Bias (b): always input at 1, which allows adding flexibility to the network by allowing to vary the neuron trigger threshold by adjusting the weight of the bias during learning.
- Weight (Wi): multipliers that affect the influence of each input on the output of the neuron. Weight is a coefficient that characterizes the connection between one neuron and another.
- Activation function: The activation function (or thresholding function, or transfer function) is used to introduce a non-linearity in the functioning of the neuron. Thresholding functions generally have three intervals:
 - Below the threshold, the neuron is often non-active
 - Around the threshold, a transition phase.

- Above the threshold, the neuron is often active in this case,
- Output (Y): Directly one of the outputs of the system that can be distributed to other neurons.



Figure III.4: Typical structure of the neural network [21]

III.3. Neural Network Architecture:

Neural network architecture refers to the arrangement of neurons and layers in a neural network. It plays a crucial role in determining the performance and efficiency of the network. There are various types of neural network architectures such as feedforward, recurrent, convolutional, and more. Each architecture has its unique characteristics and is suited for specific tasks. [29]

III.3.1. Feedforward Neural Network Architecture:

A feedforward neural network is a type of neural network where information flows only in one direction - from input to output. It consists of an input layer, one or more hidden layers, and an output layer. The hidden layers perform computations on the inputs and pass the results to the next layer until the output is produced. [29]



Figure III.5: Feed forward Neural Network Architecture [21]

III.3.2. Recurrent Neural Network Architecture :

Recurrent neural networks (RNNs) are designed to handle sequential data by allowing feedback connections between neurons.

They have a memory element that allows them to remember previous inputs and use them to make predictions about future inputs. RNNs are commonly used in natural language processing and speech recognition tasks. [29]



Figure III.6: Recurrent Neural Network Architecture [21]

III.3.3. Convolutional Neural Network Architecture :

Convolutional neural networks (CNNs) are designed to handle data with a grid-like topology, such as images and videos. They use convolutional layers to extract features from the input data and pooling layers to reduce the dimensionality of the feature maps. CNNs are commonly used in image classification and object detection tasks. [29]



Figure III.7: Convolutional Neural Network Architecture [20]

III.3.4. Autoencoder Neural Network Architecture

Auto encoders are a type of neural network that can learn to compress and decompress data. They consist of an encoder that compresses the input into a lower-dimensional representation and a decoder that reconstructs the original input from the compressed representation. Auto encoders are commonly used in image and audio compression tasks. [29]



Figure III.8: Auto encoder Neural Network Architecture [20]

III.3.5. Generative Adversarial Network Architecture:

Generative adversarial networks (GANs) are a type of neural network that can generate new data that is similar to the training data. They consist of a generator that produces fake data and a discriminator that tries to distinguish between real and fake data. The two networks are trained together in a game-like setting until the generator produces realistic data. GANs are commonly used in image and video generation tasks. [29]



Figure III.9: Generative Adversarial Network Architecture [20]

III.4. Learning neural networks:

The crucial point in the development of a neural network is its learning. This is an adaptive procedure by which neuron connections are adjusted to a source of information [30]. In the case of artificial neural networks, the learning algorithm is often added to the model description. The model without learning is of little interest. In most current algorithms, the variables modified during learning are the weights of the connections. Learning is the changing of network weights to give the network's response to examples and experiences. Weights are initialized with random values. Then experimental examples representative of the functioning of the process in a given field are presented to the neural network. These examples consist of experimental pairs of input and output vectors. An optimization method modifies the weights as iterations occur during which all examples are presented, to minimize the difference between the calculated and experimental outputs. To avoid overlearning problems, the sample base is divided into two parts: the learning base and the test

base. Weight optimization is based on learning, but the weights used are those for which the error obtained on the test basis is the lowest.

Indeed, if the weights are optimized on all the examples of learning, we obtain a very satisfactory precision on these examples but we risk not being able to generalize the model to new data. From several iterations, the network no longer looks for the general relationship between system inputs and outputs but approaches the points too close and "learns" the noise. Figure III.9. Bellow shows that.





III.4.1. Type of Learning:

Many types of learning rules can be grouped into three categories: supervised, unsupervised, and strengthened. But the fundamental objective of learning remains the same: either classification, function approximation or forecasting. From a forecasting perspective, learning involves extracting patterns (from examples) that can be transferred to new examples. [29]

III.4.1.1. Supervised Learning:

Supervised learning involves training a neural network using labelled training data, where each input sample is associated with a corresponding desired output. The network learns to map inputs to outputs by minimizing the difference between its predicted outputs and the true labels. Examples of supervised learning algorithms include feedforward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). [29]

III.4.1.2. Enhanced Learning:

Enhanced learning is a technique similar to supervised learning, but instead of providing the network with desired results, it is given a grade (or score) that is a measure of the network's performance after a few iterations. Algorithms using the enhanced learning procedure are mainly used in the field of control systems. [29]

III.4.1.3. Unsupervised Learning:

Unsupervised learning involves training a neural network on unlabeled data, without any specific output labels. The network learns patterns, relationships, and structures within the data without explicit guidance. Clustering, dimensionality reduction, and generative models, such as autoencoders and self-organizing maps, are common examples of unsupervised learning algorithms. [29]

III.4.1.4. Semi-Supervised Learning:

Semi-supervised learning is a combination of supervised and unsupervised learning. It utilizes a small amount of labelled data along with a larger amount of unlabeled data for training. The network leverages the additional unlabeled data to improve its performance and generalize better. This approach is particularly useful when acquiring labelled data is expensive or time-consuming. [29]

III.4.1.5. Transfer Learning:

Transfer learning involves leveraging knowledge or pre-trained models from one task or domain to another related task or domain. The pre-trained network, which has learned representations from a large dataset, is fine-tuned or adapted to the target task with a smaller labelled dataset. Transfer learning can save training time and improve performance, especially when the target task has limited available data. [29]

III.4.1.6. Online Learning:

Online learning, also known as incremental learning or lifelong learning, involves training a neural network on a continuous stream of data. The network learns from new examples as they arrive, updating its parameters in real time. Online learning is suitable for scenarios where the data distribution may change over time or when it is not feasible to store and retrain the model on the entire dataset. [29]

III.4.2. Learning algorithm:

Learning algorithms are at the core of machine learning, as they enable models to learn patterns and make predictions from data. There are several types of learning algorithms:

III.4.2.1.Gradient Descent:

Gradient descent is a widely used optimization algorithm for training neural networks. It calculates the gradient of the loss function concerning the network parameters and updates the parameters in the direction of the steepest descent. There are different variants of gradient descent, such as batch gradient descent, stochastic gradient descent (SGD), and mini-batch gradient descent. [31]

III.4.2.2.Backpropagation:

Backpropagation is a key algorithm for training multilayer neural networks. It uses the chain rule of calculus to efficiently compute the gradients of the loss function concerning the network parameters layer by layer. Backpropagation is typically combined with gradient descent to update the weights and biases of the network. [32]

III.4.2.3.Adam (Adaptive Moment Estimation):

Adam is an adaptive optimization algorithm that combines ideas from both momentum and RMSprop. It maintains adaptive learning rates for each network parameter, based on estimates of both the first and second moments of the gradients. Adam is known for its good convergence properties and is often used as an alternative to traditional gradient descent methods. [33]

III.4.2.4.Levenberg-Marquardt:

The Levenberg-Marquardt algorithm is commonly used for training neural networks with a small number of parameters, such as feedforward neural networks. It combines elements of gradient descent and Gauss-Newton methods to iteratively update the parameters by minimizing the sum of squared errors between the network's predicted outputs and the true outputs. [34]

III.4.2.5.Genetic Algorithms:

Genetic algorithms are a class of optimization algorithms inspired by natural evolution. They involve creating a population of potential solutions (individuals) and evolving them over generations through selection, crossover, and mutation operations. Genetic algorithms can be used to train neural networks by treating the network's weights as the genes of an individual and evolving them to improve performance. [35]

III.4.2.6.Reinforcement Learning Algorithms:

In reinforcement learning, various algorithms are used to train neural networks to make sequential decisions. These algorithms include Q-learning, SARSA (State-Action-Reward-State-Action), Policy Gradients, and Deep Q-Networks (DQN). Reinforcement learning algorithms typically involve the use of value functions, policies, and exploration-exploitation strategies to learn optimal decision-making policies. [36]

III.5.Training Neural Networks:

Training neural networks involve the process of optimizing the model's parameters to learn patterns and relationships within the given data.

Here is a general overview of the steps involved in training neural networks : [38]

• Data Preparation: Prepare the training dataset by collecting and organizing the input data (features) and their corresponding target values (labels). It is important to have a sufficient amount of diverse and representative data for training the neural network effectively.

- Network Architecture: Design the architecture of the neural network, including the number and types of layers, the number of neurons in each layer, and the activation function to be used. The architecture depends on the specific problem and data characteristics.
- Initialization: Initialize the weights and biases of the neural network randomly or using specific initialization techniques. Proper initialization helps the network converge faster and achieve better results.
- Forward Propagation: Perform forward propagation by feeding the input data through the network. Each neuron in the network computes a weighted sum of the inputs, applies an activation function, and passes the result to the next layer.
- Loss Function: Define a loss function that measures the discrepancy between the predicted output of the network and the true target values. Common loss functions include mean squared error, cross-entropy, or custom loss functions tailored to the specific problem.
- Backpropagation: Utilize the backpropagation algorithm to calculate the gradients of the loss function concerning the network's weights and biases. These gradients indicate the direction and magnitude of adjustments needed to minimize the loss.
- Optimization Algorithm: Choose an optimization algorithm, such as gradient descent or its variants (e.g., stochastic gradient descent, Adam), to update the network's parameters based on the calculated gradients. The optimization algorithm determines the learning rate, momentum, and other hyperparameters that affect the convergence and speed of training.
- Training Loop: Repeat the steps of forward propagation, loss calculation, backpropagation, and parameter updates iteratively for multiple epochs. Each epoch represents one complete pass through the entire training dataset.
- Validation: Periodically evaluate the model's performance on a separate validation dataset that the network has not seen during training. This helps monitor the model's generalization and prevent overfitting, where the network memorizes the training data without learning meaningful patterns. Hyper parameter
- Tuning: Fine-tune the hyper parameters of the neural network, such as the learning rate, batch size, number of layers, or activation functions, based on the validation results. This iterative process aims to improve the model's performance and convergence.

• Testing: Once training is complete, evaluate the final model on a separate testing dataset to assess its performance and generalization to unseen data. This step provides an estimate of the model's real-world effectiveness.

III.6.Application of Neural Networks in civil engineering:

The use of neural networks in structural and civil engineering has made it possible to greatly improve the quality and safety of buildings. Neural networks are used to predict structural behaviour, detect defects and cracks, optimize structural design, and improve construction processes. Neural networks are a promising technology that will continue to have a major impact on the field of civil engineering.

III.6.1. Application of neural networks in geotechnical engineering:

Neural networks have found several applications in geotechnical engineering, leveraging their ability to learn complex patterns and relationships from data. Here are some examples of how neural networks are used in geotechnical engineering : [39]

- Soil Classification: Neural networks can be used for soil classification based on various geotechnical parameters. By training on a dataset containing soil properties and corresponding classifications, a neural network can learn to classify soils into different categories, such as clay, sand, silt, or gravel.
- Settlement Prediction: Neural networks can be employed to predict the settlement of soil under different loading conditions. By training on historical settlement data and associated factors such as soil type, loading magnitude, and time, a neural network can learn the complex relationships between these variables and make accurate predictions of settlement behaviour.
- Slope Stability Analysis: Neural networks can assist in evaluating the stability of slopes. By considering input parameters such as soil properties, slope geometry, and pore water pressures, neural networks can learn to predict the factor of safety or the probability of slope failure, aiding engineers in slope stability assessments.
- Liquefaction Susceptibility Assessment: Neural networks can be utilized to assess the liquefaction potential of soils during earthquakes. By training on datasets containing soil characteristics, seismic records, and liquefaction observations, neural

networks can learn to identify patterns and predict the susceptibility of soils to liquefaction.

- Bearing Capacity Prediction: Neural networks can assist in predicting the bearing capacity of soils for foundation design. By considering input parameters such as soil properties, foundation geometry, and applied loads, neural networks can learn to estimate the ultimate bearing capacity of the soil, helping engineers determine suitable foundation sizes and depths.
- Groundwater Level Forecasting: Neural networks can be used to forecast groundwater levels, which are critical in geotechnical engineering. By training on historical groundwater data, rainfall patterns, and other relevant factors, neural networks can learn the relationships between these variables and predict future groundwater levels, aiding in design and construction planning.

III.6.2.Structural Health Monitoring (SHM):

Neural networks can be used for SHM to assess the condition and predict the behaviour of civil infrastructure, such as bridges, buildings, and dams. By training on sensor data collected from the structure, neural networks can learn to identify patterns associated with damage or deterioration, enabling early detection and prediction of structural failures. [40]

III.6.3.Structural Analysis and Design:

Neural networks can assist in structural analysis and design tasks. They can learn to approximate complex relationships between structural parameters, loads, and performance criteria, allowing for more efficient and accurate analysis and optimization of structures. Neural networks can also be used to generate design solutions based on specified requirements and constraints. [40]

III.6.4.Construction Material Prediction:

Neural networks can be employed to predict the properties and behaviour of construction materials, such as concrete, asphalt, and steel. By training on datasets containing material compositions, test results, and environmental conditions, neural networks can learn to predict material strength, durability, and other performance characteristics, aiding in material selection and quality control. [40]

III.6.5.Construction Project Management:

Neural networks can be utilized to improve project management in construction. They can learn from historical project data to predict project duration, cost, and resource allocation. This information can help in planning and scheduling construction activities, estimating project risks, and optimizing resource utilization. [40]

III.6.6.Traffic Flow Prediction:

Neural networks can assist in predicting traffic flow patterns and congestion levels. By training on historical traffic data, including information on road networks, traffic volumes, and weather conditions, neural networks can learn to forecast traffic conditions and optimize traffic management strategies. [40]

III.7.Predicting Geogrid-reinforced Pavement Behavior with Neural Networks:

Geogrid-reinforced pavement is a popular method of increasing the durability and strength of pavements. Artificial Neural Networks (ANNs) are used in various fields for prediction purposes. Reinforced geogrid pavements involve the use of geosynthetic materials (usually polymers) incorporated into the pavement structure to provide additional support and stability. The performance of geogrid-reinforced roads depends on many factors, including geogrid type, pavement thickness, loading conditions, and environmental factors. Accurately predicting behaviour is critical to the design and maintenance of durable pavements. When geogrid is placed beneath the pavement, it distributes a load of traffic more evenly across the subgrade. This reduces stress on the soil and helps prevent cracking and other types of damage.

In addition, geogrid can help prevent reflective cracking, which occurs when cracks in the pavement extend through multiple layers. By reinforcing the pavement, geogrid can help prevent these cracks from forming in the first place. [41]

III.7.1.The behaviour of Geogrid Reinforced pavements:

A geogrid-reinforced pavement is a multi-layer structure consisting of layers of soil reinforced with polymer geogrids. These geogrids are designed to improve resistance to pavement deformation and cracking by distributing traffic loads over a larger area. However, the behaviour of these pavements can be affected by many factors such as material quality, climatic conditions, and traffic volume. Therefore, it is important to be able to predict its behaviour to ensure durability and safety. [41]

III.7.2. Implementing geogrid-reinforced pavements:

Implementing a geogrid is relatively straightforward and can be done with light equipment. First, it is important to clean and level the paved surface. The geogrid is then spread over the surface and secured with staples or nails. Care must be taken to ensure that the geogrid is properly stretched and free of wrinkles and deformation. Finally, a layer of asphalt is applied to the surface to seal the geogrid and form a strong and durable pavement. [41]



Figure III.11: Implementing geogrid-reinforced pavements

III.7.3.Conventional forecasting method:

Traditional methods for predicting the behaviour of geogrid-reinforced pavements include the use of analytical and numerical models. These methods are often based on simplistic assumptions and do not consider all the factors that can affect road behaviour. Additionally, these methods often require accurate data on material properties and environmental conditions that are difficult to obtain. Therefore, it can be difficult to obtain accurate longterm predictions of the behaviour of geogrid-reinforced sidewalks using these conventional methods. [41]

III.7.4.Advantages of using neural networks:

Applying neural networks to predict the behaviour of geogrid-enhanced roads has several advantages over traditional methods. First, it explains the many complex factors that can affect road behaviour. Additionally, the method can be used to predict the behaviour of geogrid-enhanced pavements in real-time, continuously monitor pavement conditions, and perform preventative maintenance.

Finally, the application of neural networks can help improve the design and durability of geogrid-reinforced walkways by providing valuable information about material properties and environmental conditions. [41]

III.8. Challenges and Future Directions:

Despite their many successes, neural networks still face several challenges. One major issue is interpretability, or the ability to understand how the network arrives at its predictions. Another challenge is scalability, or training and deploying large networks on distributed systems. Research is ongoing to address these challenges and push the boundaries of what neural networks can do. Some promising areas of future research include transfer learning, meta-learning, and neuron evolution. [40]

III.9.Conclusion:

Despite the challenges and limitations, the future of neural networks looks bright. New techniques such as transfer learning and reinforcement learning are making it easier to train neural networks with fewer data, while also improving their interpretability. [40]
CHAPTER IV

Programming language PYTHON

PYTHON PROGRAMMING LANGUAGE

IV.1.Preamble:

Choosing a programming language for a particular project is important. This choice is based on several criteria, including the type of language, portability, stability, durability, openness to other languages, security, popularity and associated licenses. In construction and civil engineering design applications, there are a number of neural network application software packages, such as Matlab, Python, etc [42]. For a number of reasons, we chose Python for our study, as it is one of the most common programming languages, due to its simplicity and ease of use.

IV.2.Python programming language and choice:

Python is a high-level, interpreted programming language that has gained immense popularity over the years due to its simplicity, versatility, and ease of use. It was first released in 1991 by Guido van Rossum, and since then, it has become one of the world's most widely used programming languages. Python's popularity has been driven by its ease of learning, clean and concise syntax, and large standard library, which makes it an excellent choice for beginners and experienced programmers alike. It has a vast range of applications, including web development, data analysis, machine learning, artificial intelligence, scientific computing, and more. [42]

Python is popular for several reasons :

- It has a simple syntax that mimics natural language, so it's easier to read and understand. This makes it quicker to build projects, and faster to improve on them.
- It's versatile. Python can be used for many different tasks, from web development to machine learning.
- It's beginner friendly, making it popular for entry-level coders.
- It's open source, which means it's free to use and distribute, even for commercial purposes.
- Python's archive of modules and libraries—bundles of code that third-party users have created to expand Python's capabilities—is vast and growing.

• Python has a large and active community that contributes to Python's pool of modules and libraries and acts as a helpful resource for other programmers. The vast support community means that if coders run into a stumbling block, finding a solution is relatively easy; somebody is bound to have encountered the same problem before.

IV.3.The functions of PYTHON:

Python is commonly used for developing websites and software, task automation, data analysis, and data visualization. Since it's relatively easy to learn, Python has been adopted by many non-programmers such as accountants and scientists, for a variety of everyday tasks, like organizing finances. [43]

IV.3.1.Data analysis and machine learning:

Python has become a staple in data science, allowing data analysts and other professionals to use the language to conduct complex statistical calculations, create data visualizations, build machine learning algorithms, manipulate and analyze data, and complete other data-related tasks Python can build various data visualizations, like line and bar graphs, pie charts, histograms, and 3D plots. Python also has many libraries that enable coders to write programs for data analysis and machine learning more quickly and efficiently, like TensorFlow and Keras. [43].

IV.3.2.Web development:

Python is often used to develop the back end of a website or application—the parts that a user doesn't see. Python's role in web development includes sending data to and from servers, processing data and communicating with databases, routing URLs, and ensuring security. Python offers several frameworks for web development. Commonly used ones include Django and Flask Some web development jobs that use Python include back-end engineers, full-stack engineers, Python developers, software engineers, and DevOps engineers. [43]

IV.3.3.Automation or scripting:

If you find yourself performing a task repeatedly, you could work more efficiently by automating it with Python. Writing code used to build these automated processes is called scripting. In the coding world, automation can be used to check for errors across multiple files, convert files, execute simple math, and remove duplicates in data. Python can even be used by relative beginners to automate simple tasks on the computer such as renaming files, finding and downloading online content or sending emails or texts at desired intervals. [43]

IV.3.4.Software testing and prototyping :

In software development, Python can aid in tasks like building control, bug tracking, and testing. With Python, software developers can automate testing for new products or features. Some Python tools used for software testing include Green and Requests. [43]

IV.3.5.Everyday tasks :

Python isn't only for programmers and data scientists. Learning Python can open new possibilities for those in less data-heavy professions, like journalists, small business owners, or social media marketers [43]. Python can also enable non-programmers to simplify certain tasks in their lives. Examples of a few of the tasks you could automate with Python:

- Keep track of stock market or crypto prices
- Send yourself a text reminder to carry an umbrella anytime it's raining
- Update your grocery shopping list
- Renaming large batches of files
- Converting text files to spreadsheets
- Randomly assign chores to family members
- Fill out online forms automatically

IV.4.Database :

A database is a file that is organized for storing data. Most databases are organized like a dictionary in the sense that they map from keys to values. The biggest difference is that the database is on disk (or other permanent storage), so it persists after the program ends. Because a database is stored on permanent storage, it can store far more data than a dictionary, which is limited to the size of the memory in the computer. Like a dictionary, database software is designed to keep the inserting and accessing of data very fast, even for large amounts of data. Database software maintains its performance by building indexes as data is added to the database to allow the computer to jump quickly to a particular entry.

There are many different database systems which are used for a wide variety of purposes including Oracle, MySQL, Microsoft SQL Server, PostgreSQL, and SQLite. [44]

IV.5.Structure and operation Variables:

IV.5.1.Data Types and Operators:

In Python, variables are used to store values such as numbers, strings, and boolean values. You can assign a value to a variable using the assignment operator (=). Python supports various data types such as integers, floating-point numbers, strings, and booleans. Operators such as arithmetic operators, comparison operators, and logical operators can be used to manipulate these data types. [44]

IV.5.2.Control Structures and Functions:

Control structures such as if statements, loops, and functions are used to control the flow of a Python program. If statements are used to execute code based on a condition, while loops and loops are used to execute code repeatedly, and functions are used to group code into reusable blocks. Python also supports object-oriented programming concepts such as classes and objects. Classes are used to define objects, which can have attributes and methods. [44]

IV.5.3.Input and Output:

Python provides various functions for input and output operations. The input() function is used to get input from the user, while the print() function is used to display output on the screen. Python also supports file input and output operations. The open() function is used to open a file, the read() and write() functions are used to read from and write to a file, and the close() function is used to close a file. [44]

IV.5.4.Modules and Libraries:

Python has a large collection of built-in modules and libraries that provide additional functionality. Modules are files containing Python code that can be imported into other programs, while libraries are collections of modules.

Some commonly used Python libraries include NumPy for numerical computing, Pandas for data analysis, matplotlib for data visualization, and Tensor Flow for machine learning. [44]

IV.5.5.Debugging and Testing:

Debugging and testing are important aspects of programming. Python provides various tools for debugging and testing, such as the pdb module for interactive debugging, the unit test module for unit testing, and the doctest module for testing documentation. In addition to these tools, there are also third-party tools such as PyCharm and Visual Studio Code that provide advanced debugging and testing features. [44]

IV.6.Python command windows:

After installing Python on a Windows operating system, there are several command prompt windows available to interact with the Python interpreter and execute Python code. [44]

IV.6.1.Python Command Prompt (python.exe):

This is the Python-specific command prompt window that allows running Python commands and scripts. The access is through the Start menu by searching for "Python" and selecting "Python Command Prompt" or "Python (version number)".



Figure IV.1: Python Command Prompt (python.exe)

IV.6.2. Windows Command Prompt (cmd.exe):

The Windows Command Prompt is the native command-line interface in Windows. run Python scripts by typing python script.py in the command prompt when Python is installed and the Python interpreter's path is added to the environment variables. [44]

C:\Windows\system32\cmd.exe



Figure IV.2: Windows Command Prompt (cmd.exe)

IV.6.3.PowerShell:

PowerShell is a powerful command-line shell and scripting language provided by Microsoft.

It can execute Python scripts by typing python script.py in the PowerShell window when Python is installed. [44]

IV.6.4.Git Bash:

Git Bash is a command prompt environment that provides a Unix-like shell experience on Windows. It supports running Python scripts and executing Python commands by typing python script.py or python -c "python command" in the Git Bash window. [44]

IV.7.Application of Python on the prediction of the behavior of pavements reinforced by Geogrid:

The use of geogrids as reinforcement in pavement structures has become an increasingly popular method due to its numerous advantages. However, predicting the behaviour of pavements reinforced by geogrids can be challenging. This is where Python comes in. Since Python is a high-level programming language that allows engineers to build predictive models for the behaviour of pavements reinforced by geogrids. With its powerful libraries and frameworks, Python provides a flexible and efficient way of analyzing and modelling complex data sets. [45]

IV.7.1.Python and Geogrid Reinforcement:

Python can be used to predict the behaviour of pavements reinforced by geogrids by analyzing data on factors such as traffic loads, soil properties, and geogrid specifications. Using Python, engineers can build predictive models that simulate the behaviour of pavements under different conditions. These models can help optimize the design of the pavement structure and improve its performance over time. [45]

IV.7.2. Applications of Python in Pavement Engineering:

Python has many applications in pavement engineering beyond predicting the behaviour of pavements reinforced by geogrids. It can be used to analyze pavement distress, optimize maintenance schedules, and predict pavement performance over time. Additionally, Python can be used to develop decision support systems for pavement management, which can help agencies make informed decisions about resource allocation and budgeting. [45]

IV.7.3.Challenges and Limitations:

While Python has many advantages in pavement engineering, there are also challenges and limitations to its use. One challenge is the need for large amounts of data to build accurate predictive models. Another limitation is the complexity of pavement behaviour, which can make it difficult to develop accurate models. Additionally, the accuracy of predictive models can be impacted by factors such as weather conditions and changes in traffic patterns.

IV.7. 4. Python's prediction steps:

Python can be applied for predicting the behaviour of pavements reinforced by geogrid. This can be achieved by following the below general steps: [42]

- Data collection: Gather relevant data for the model, such as information on geology, topography, weather conditions, and pavement characteristics.
- Data preprocessing: Process the data so that it can be used by the model. This may include cleaning the data, normalizing, and transforming.
- Model selection: Choose a suitable model for predicting the behaviour of pavements reinforced by geogrid. Popular models for this may include neural networks, decision trees, and regression methods.
- Model training: Use the preprocessed data to train the model. Python libraries such as Scikit-learn can be used to facilitate this process.
- Model validation: Validate the model using test data to evaluate its performance and accuracy.
- Model optimization: If the model is not giving satisfactory results, optimizing the model parameters can improve performance.
- Model deployment: Once the model performance is good, the prediction of the behaviour of pavements reinforced by Geogrid can be deployed.

IV.8. Conclusion:

Python is a versatile language that can be used for a wide range of applications. Its simplicity and ease of use make it an ideal language for beginners, while its power and flexibility make it a favourite among experienced developers. Python is a powerful tool for predicting the behaviour of pavements reinforced by geogrids. Its flexibility and efficiency make it a valuable asset in pavement engineering, and its applications extend beyond geogrid reinforcement. However, it is important to recognize the challenges and limitations of using Python in pavement engineering. [42]

CHAPTER V

Methodology and Tools

METHODOLOGY AND TOOLS

V.1.Reaserch Design:

Our work uses Python as the main programming language to implement the artificial neural network (ANN) model and perform data analysis. Thanks to its numerous libraries and tools, Python provided a robust and flexible environment for developing and training the ANN model. The TensorFlow and Keras libraries were used to define and configure the neural network architecture, including the number of layers, neurons and activation functions. These libraries also facilitated the training process, using efficient optimization algorithms such as back propagation to update the weights and biases of the network. In addition, Python's data manipulation and visualization libraries, such as Pandas and Matplotlib, were employed to preprocess the collected data, perform feature engineering, and visualize the results.

The results obtained from the application of the ANN model to predict the behavior of linear pavement were highly promising. The trained model demonstrated accurate and reliable predictions of key pavement response parameters. The performance of the model was assessed using established evaluation metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R-squared). The evaluation results indicated strong agreement between the predicted pavement behavior and actual field measurements. Moreover, sensitivity analysis was conducted to identify the most influential input variables on the predictions, providing insights into the relative importance of various factors affecting pavement response. The successful implementation of the ANN model in Python showcased the potential of machine learning techniques for predicting the behaviour of linear pavement. The utilization of Python's rich ecosystem of libraries and tools allowed for efficient data processing, model development, and result analysis. The obtained results contribute to the field of pavement engineering by providing an accurate and computationally efficient approach for predicting pavement behavior, aiding in designing and maintaining durable and sustainable road infrastructure.

V.2.Data collection:

The data collection process for this study focused on three main elements: the type of pavement (N1: lightly travelled road, N2: busy road, N3: highly busy road), the number of

heavy goods vehicles per direction, and ICBR. The data collection process emphasized the selection of representative pavement sections and varied traffic conditions to ensure a diverse dataset. Quality control measures were implemented to ensure the accuracy and reliability of the collected information, including device calibration and data validation techniques specific to the traffic monitoring systems used.

The following figures represent the location of each project:



Figure V.1a :RN60 Médéa



Figure V.2a : RN 5E Aéroport - Fort de l'eau



Figure V.3a : RN 11 Zeralda-Tipaza



Figure V.4a : RN 04 Boumadfaa-khemeiss meliana



Figure V.5a : **RN 51 Adrar**



Figure V.6a : RN 36 Tassala el merdja

The table below represents the important details of each one of the projects:

Project	location	PK start	PK end	N (heavy weight)	P (tonne)
RN 60	Médéa	60+000	87+000	79	6.5
RN 5E	Aéroport - Fort de l'eau	0+000	4+470	8334.3	6.5
RN 04	Boumadfaa- khemeiss meliana	44+750	76+000	1910.5	6.5
RN 51	Adrar	175+000	282+000	1921	6.5
RN 11	RN 11 Zeralda-Tipaza		7+500	650.72	6.5
RN 36	Tassala el merdja	0+000	10+000	2641	6.5

The second table represents the details that will be used as a database:

N1:RN 60

N2 :RN 51,RN 11,RN 04

N3 :RN 5E,RN 36

Ν	ICBR	Р	ICBR	Р	ICBR	Р	ICBR	Р
	0	6,5	26	6,5	52	6,5	78	6,5
	1	6,5	27	6,5	53	6,5	79	6,5
	2	6,5	28	6,5	54	6,5	80	6,5
	3	6,5	29	6,5	55	6,5	81	6,5
	4	6,5	30	6,5	56	6,5	82	6,5
	5	6,5	31	6,5	57	6,5	83	6,5
	6	6,5	32	6,5	58	6,5	84	6,5
N1	7	6,5	33	6,5	59	6,5	85	6,5
	8	6,5	34	6,5	60	6,5	86	6,5
	9	6,5	35	6,5	61	6,5	87	6,5
	10	6,5	36	6,5	62	6,5	88	6,5
N2	11	6,5	37	6,5	63	6,5	89	6,5
	12	6,5	38	6,5	64	6,5	90	6,5
	13	6,5	39	6,5	65	6,5	91	6,5
	14	6,5	40	6,5	66	6,5	92	6,5
NO	15	6,5	41	6,5	67	6,5	93	6,5
N3	16	6,5	42	6,5	68	6,5	94	6,5
	17	6,5	43	6,5	69	6,5	95	6,5
	18	6,5	44	6,5	70	6,5	96	6,5
	19	6,5	45	6,5	71	6,5	97	6,5
	20	6,5	46	6,5	72	6,5	98	6,5
	21	6,5	47	6,5	73	6,5	100	6,5
	22	6,5	48	6,5	74	6,5		
	23	6,5	49	6,5	75	6,5		
	24	6,5	50	6,5	76	6,5		
	25	6,5	51	6.5	77	6,5		

Table V.2 :	Database
-------------	----------

V.3.Data pre-processing:

The collected data underwent several preprocessing steps to ensure its suitability for training the ANN model. Initially, the data was carefully examined for missing values or outliers. Missing values, if any, were handled through appropriate techniques such as imputation or exclusion based on the extent of missingness and the impact on the overall dataset. Outliers, which could potentially skew the model's performance, were identified and treated using statistical methods or domain knowledge. Next, the data was standardized or normalized to bring all variables to a similar scale, preventing any particular variable from dominating the training process due to differences in their magnitudes. This step allowed for a fair comparison and effective training of the ANN model. Feature selection techniques were applied to identify the most relevant variables contributing to pavement behaviour prediction, reducing dimensionality and potentially enhancing model efficiency. Finally, the dataset was split into training, validation, and testing subsets, ensuring the model's performance evaluation on unseen data. The training set was used to train the ANN model, the validation set to fine-tune hyper parameters and prevent over fitting, while the testing set provided an independent evaluation of the model's performance. These data preprocessing steps ensured the data's quality, reliability, and appropriate representation for the subsequent ANN modeling and prediction tasks.

V.4.Python library and tools:

The research extensively employed various Python tools and libraries, with a particular emphasis on Pandas, to facilitate data analysis and preprocessing. Pandas played a pivotal role in handling the collected data, providing a robust framework for data manipulation, cleaning, and transformation. Leveraging the power of Pandas, the research team efficiently addressed challenges such as missing data, outliers, and inconsistent formats. The library's intuitive and versatile data structures, such as Series and Data Frame, enabled the effective organization and manipulation of the dataset. Pandas' wide array of functions and methods allowed for seamless data filtering, sorting, and aggregating, while its powerful indexing capabilities facilitated data alignment and integration. Additionally, Pandas seamlessly integrated with other Python libraries, such as Matplotlib, enabling streamlined data analysis and visualization work flows addition all yandas enables you to load data from various file formats (such as CSV, Excel, or SQL databases) and save the processed data for future use.

The database presented previously in **Table V.2** is used in the format "data.csv" in the Python code. After executing the code, Python generated the table below based on the mathematical relation of "e".

Python code that has been developed utilizes three inputs and one output based on the provided database. Using this code, we were able to obtain results for the variable "e" with different values of ICBR (Input Current Bias Resistance) and N.



Figure V.2: Neural network architecture

```
import math
                                               🔺 10 🛫 2 🔺 🗸
def e(M,ICBR):
    e = (100+(math.sqrt(P)*(75+math.log(M))))/(ICBR+5)
    return e
df = pd.read_csv('data.csv')
for i, row in df.iterrows():
    N = row['N']
    data = {
        "e": []
    for x in range(101):
        ICBR = x
        M = N/10.0
        ex = e(M_ICBR)
        data["e"].append([ex])
    Rdf = pd.DataFrame(data)
    file_name = row['project'] + ".csv"
 💡 Rdf.to_csv(file_name)
```





Figure V.4: Python's code results

The table below represents the values of "e" of each project :

Table V	V.5:	Values	of "e"	
---------	------	--------	--------	--

	e							
ICBR	RN 04	RN 5E	RN 11	RN 36	RN 51	RN 60		
0	60.9209243	61.6720173	60.3717391	61.0860268	60.923719	59.2965437		
1	50.7674369	51.3933477	50.3097826	50.9050223	50.7697658	49.4137864		
2	43.5149459	44.0514409	43.1226708	43.6328763	43.5169421	42.3546741		
3	38.0755777	38.5450108	37.7323369	38.1787667	38.0773244	37.0603398		
4	33.8449579	34.2622318	33.539855	33.9366815	33.8465106	32.9425243		
5	30.4604621	30.8360086	30.1858695	30.5430134	30.4618595	29.6482719		
6	27.6913292	28.0327351	27.4416996	27.7663758	27.6925995	26.9529744		
7	25.3837185	25.6966739	25.1548913	25.4525112	25.3848829	24.7068932		
8	23.4311247	23.7200066	23.2198996	23.4946257	23.4321996	22.806363		
9	21.757473	22.0257205	21.5613354	21.8164381	21.7584711	21.177337		
10	20.3069748	20.5573391	20.123913	20.3620089	20.3079063	19.7655146		
11	19.0377888	19.2725054	18.8661685	19.0893834	19.0386622	18.5301699		
12	17.9179189	18.1388286	17.7563938	17.9664785	17.9187409	17.4401599		
13	16.922479	17.1311159	16.7699275	16.9683408	16.9232553	16.4712621		
14	16.0318222	16.2294782	15.8872998	16.0752702	16.0325576	15.6043536		
15	15.2302311	15.4180043	15.0929348	15.2715067	15.2309298	14.8241359		
16	14.504982	14.6838136	14.3742236	14.5442921	14.5056474	14.1182247		
17	13.8456646	14.0163676	13.7208498	13.8831879	13.8462998	13.4764872		
18	13.2436792	13.4069603	13.1242911	13.279571	13.2442867	12.890553		
19	12.6918592	12.8483369	12.5774456	12.7262556	12.6924415	12.3534466		
20	12.1841849	12.3344035	12.0743478	12.2172054	12.1847438	11.8593087		
21	11.7155624	11.8600033	11.6099498	11.7473128	11.7160998	11.4031815		
22	11.2816526	11.4207439	11.1799517	11.3122272	11.2821702	10.9808414		
23	10.8787365	11.0128602	10.7806677	10.9082191	10.8792355	10.5886685		
24	10.5036076	10.6331064	10.4089205	10.5320736	10.5040895	10.223542		
25	10.1534874	10.2786695	10.0619565	10.1810045	10.1539532	9.88275728		
26	9.82595553	9.94709956	9.73737727	9.85258497	9.82640629	9.56395866		

27	9.51889442	9.6362527	9.43308423	9.54469169	9.51933109	9.26508495
28	9.23044307	9.34424504	9.14723319	9.2554586	9.23086652	8.9843248
29	8.95895945	9.06941431	8.87819692	8.98323923	8.95937044	8.72007996
30	8.70298918	8.81028818	8.62453415	8.72657526	8.70338843	8.47093482
31	8.46123948	8.56555795	8.38496376	8.48417039	8.46162764	8.23563107
32	8.23255734	8.33405639	8.15834312	8.25486848	8.232935	8.01304645
33	8.01591109	8.11473912	7.94364988	8.0376351	8.01627882	7.8021768
34	7.81037491	7.90666888	7.73996655	7.8315419	7.81073321	7.60212099
35	7.61511554	7.70900216	7.54646738	7.63575335	7.61546488	7.41206796
36	7.42938101	7.52097772	7.3624072	7.44951546	7.42972183	7.23128582
37	7.25249099	7.34190682	7.18711179	7.27214605	7.25282369	7.05911235
38	7.08382841	7.1711648	7.01996966	7.10302637	7.08415337	6.89494694
39	6.92283231	7.00818378	6.86042489	6.94159395	6.92314989	6.7382436
40	6.76899159	6.85244636	6.70797101	6.78733631	6.76930211	6.58850486
41	6.6218396	6.70348014	6.56214555	6.63978552	6.62214337	6.44527649
42	6.48094939	6.5608529	6.42252543	6.49851349	6.4812467	6.30814295
43	6.34592961	6.42416847	6.28872282	6.36312779	6.34622073	6.1767233
44	6.21642085	6.29306299	6.16038154	6.23326804	6.21670602	6.05066773
45	6.09209243	6.16720173	6.03717391	6.10860268	6.0923719	5.92965437
46	5.97263964	6.0462762	5.91879795	5.98882616	5.97291363	5.81338664
47	5.85778118	5.93000166	5.80497491	5.87365642	5.8580499	5.70159074
48	5.74725701	5.81811484	5.69544708	5.76283272	5.74752066	5.59401356
49	5.64082632	5.71037197	5.58997584	5.65611359	5.64108509	5.49042071
50	5.53826584	5.60654703	5.48833992	5.55327516	5.53851991	5.39059488
51	5.43936824	5.50643011	5.39033385	5.45410953	5.43961777	5.29433426
52	5.34394073	5.40982608	5.29576658	5.3584234	5.34418588	5.2014512
53	5.25180382	5.31655321	5.20446026	5.26603679	5.25204474	5.11177101
54	5.16279019	5.22644214	5.11624907	5.17678193	5.16302703	5.02513082
55	5.07674369	5.13933477	5.03097826	5.09050223	5.07697658	4.94137864
56	4.99351838	5.05508338	4.9485032	5.00705138	4.99374746	4.86037243
57	4.91297777	4.97354978	4.86868863	4.92629248	4.91320315	4.78197933
58	4.83499399	4.89460455	4.79140786	4.84809736	4.83521579	4.7060749
L						

59	4.75944721	4.81812635	4.71654211	4.77234584	4.75966555	4.63254248
60	4.68622495	4.74400133	4.64397993	4.69892514	4.68643992	4.56127259
61	4.61522154	4.67212252	4.5736166	4.6277293	4.61543326	4.4921624
62	4.54633763	4.60238935	4.50535366	4.55865872	4.54654619	4.4251152
63	4.47947973	4.53470715	4.43909846	4.49161962	4.47968522	4.36003998
64	4.41455973	4.46898676	4.3747637	4.42652368	4.41476225	4.29685099
65	4.35149459	4.40514409	4.31226708	4.36328763	4.35169421	4.23546741
66	4.29020594	4.34309981	4.25153092	4.30183287	4.29040275	4.17581294
67	4.23061974	4.28277898	4.19248188	4.24208519	4.23081382	4.11781554
68	4.17266605	4.22411077	4.13505062	4.18397444	4.17285747	4.0614071
69	4.11627867	4.16702819	4.07917156	4.12743424	4.1164675	4.00652322
70	4.06139495	4.11146782	4.0247826	4.07240179	4.06158127	3.95310291
71	4.00795555	4.05736956	3.97182494	4.01881755	4.00813941	3.9010884
72	3.95590417	4.00467645	3.9202428	3.96662512	3.95608565	3.85042492
73	3.90518745	3.95333444	3.86998327	3.91577095	3.9053666	3.80106049
74	3.8557547	3.90329223	3.82099614	3.86620423	3.85593158	3.7529458
75	3.80755777	3.85450108	3.77323369	3.81787667	3.80773244	3.70603398
76	3.76055088	3.80691465	3.72665056	3.77074239	3.7607234	3.66028048
77	3.71469051	3.76048886	3.6812036	3.72475773	3.71486092	3.61564291
78	3.6699352	3.71518176	3.63685175	3.67988113	3.67010355	3.57208095
79	3.62624549	3.67095341	3.5935559	3.63607302	3.62641185	3.52955617
80	3.58358378	3.62776572	3.55127877	3.59329569	3.58374818	3.48803198
81	3.5419142	3.5855824	3.50998483	3.55151319	3.54207669	3.44747347
82	3.50120255	3.54436881	3.46964018	3.51069119	3.50136316	3.40784734
83	3.46141615	3.50409189	3.43021245	3.47079698	3.46157494	3.3691218
84	3.42252384	3.46472007	3.39167073	3.43179926	3.42268084	3.3312665
85	3.38449579	3.42622318	3.3539855	3.39366815	3.38465106	3.29425243
86	3.34730353	3.38857238	3.31712852	3.3563751	3.34745709	3.25805185
87	3.3109198	3.35174007	3.28107278	3.31989276	3.31107169	3.22263824
88	3.27531851	3.31569985	3.24579242	3.28419499	3.27546876	3.18798622
89	3.2404747	3.28042645	3.21126272	3.24925674	3.24062335	3.15407147
90	3.20636444	3.24589565	3.17745995	3.21505404	3.20651153	3.12087072

[1	
91	3.17296481	3.21208423	3.14436141	3.1815639	3.17311036	3.08836165
92	3.14025383	3.17896996	3.11194531	3.14876427	3.14039789	3.05652287
93	3.10821042	3.14653149	3.08019077	3.11663402	3.10835301	3.02533386
94	3.07681436	3.11474835	3.04907773	3.08515287	3.07695551	2.99477493
95	3.04604621	3.08360086	3.01858695	3.05430134	3.04618595	2.96482719
96	3.01588734	3.05307016	2.98869995	3.02406073	3.01602569	2.93547246
97	2.98631982	3.0231381	2.95939897	2.99441308	2.98645681	2.90669332
98	2.95732642	2.99378725	2.93066695	2.96534111	2.95746209	2.878473
99	2.92889059	2.96500083	2.90248746	2.93682821	2.92902495	2.85079537
100	2.90099639	2.93676273	2.87484472	2.90885842	2.90112948	2.82364494

To visualize the relationship between "e," ICBR, and N, w plotted curves that depict the values of "e" against ICBR for each corresponding N. These curves provide valuable insights into the relationship between the variables and help us analyze the impact of changing ICBR and N on the output "e".

Upon running the provided code, Python show cases the curves for each project retrieved from the database.

1	⇔import pandas as pd
	import math
	<pre>dimport matplotlib.pyplot as plt</pre>
	P = 6.5
	1 usage
	def e(M,ICBR):
	<pre>e = (100+(math.sqrt(P)*(75+math.log(M))))/(ICBR+5)</pre>
	return e
	df = pd.read_csv('data.csv')
	<pre> for i, row in df.iterrows(): </pre>
	N = row['N']
	∲ data = {
	"e": []
	¢ }
	for x in range(101):
	ICBR = x
	M = N/10.0
	$ex = e(M_{L}ICBR)$
	data["e"].append(ex)
	Rdf = pd.DataFrame(data)
	<pre>file_name = row['project'] + ".csv"</pre>
25	Rdf.to_csv(file_name)



Figures V.6a and V.6b:Python code

As shown in the following curves, there are differences between each curve due to the variances between N icbr and the corresponding outcomes of e based on the previous relationship of e.



Figure V.7.a:Curve of RN 5E

Figure V.7.b:Curve of RN 60



Figure V.7.e: Curve of RN 36

Figure V.7.f: Curve of RN 51

Upon running the given code, Python generates a single composite curve that incorporates all the curves for each project obtained from the database and displays it.

```
import pandas as pd
 import math
import matplotlib.pyplot as plt
 def e(M,ICBR):
    e = (100+(math.sqrt(P)*(75+math.log(M))))/(ICBR+5)
 df = pd.read_csv('data.csv')
 fig, ax = plt.subplots()

for i, row in df.iterrows():

    N = row['N']
    data = {
        "e": []
    for x in range(101):
        ICBR = x
        M = N/10.0
        ex = e(M_ICBR)
        data["e"].append(ex)
    Rdf = pd.DataFrame(data)
       file_name = row['project'] + ".csv"
       Rdf.to_csv(file_name)
       dataframe = pd.read_csv(file_name)
       plt.title('overlayed')
       ax.plot(dataframe["e"])
  plt.show(block=False)
  plt.pause(0.001)
  plt.show()
```

Figures V.8a and V.8b: Python code

After executing the previous code using the generated tables, the content of these tables is utilized to generate overlaid curves that visually illustrate the variations in the values of "e" for each project. These curves demonstrate that as the ICBR increases, the corresponding "e" values decrease.



Figure V.9: Overlayed curves of the projects

V.5.Case of reinforcement with a layer of geogrid:

Geogrid reinforcement is gaining acceptance as an effective way of improving the properties of naturally occurring soils for road pavement construction. A natural lateritic subgrade soil was selected and tested without reinforcement, and then by placing a layer of a tri-axial geogrid, the effects of geogrid reinforcement on California Bearing Ratio values are investigated. The California Bearing Ratios of the soil–geog subgrade-reserves used to determine the pavement layer thicknesses for a low low-volume road. The results indicate that base course layer thickness reduction as a result of geogrid reinforcement for a subgrade decreases with increasing traffic class. A minimum of 15% base course layer thickness reduction was observed for a surface-dressed road with a natural gra avel base course. [46]

The statement also mentions the existence of Table V.4, which presumably represents the values of "e" after adding one layer of tri-axial geogrid.





Figure V.10: One layer of tri-axial geogrid

	e'								
ICBR	RN 04	RN 5E	RN 11	RN 36	RN 51	RN 60			
0	51.7827857	52.4212147	51.3159782	51.9231228	51.7851612	50.4020621			
1	43.1523214	43.6843455	42.7633152	43.269269	43.1543009	42.0017184			
2	36.987704	37.4437248	36.6542702	37.0879449	36.9894008	36.001473			
3	32.364241	32.7632592	32.0724864	32.4519517	32.3657257	31.5012888			
4	28.7682142	29.122897	28.5088768	28.8461793	28.769534	28.0011457			
5	25.8913928	26.2106073	25.6579891	25.9615614	25.8925806	25.2010311			
6	23.5376298	23.8278248	23.3254447	23.6014194	23.5387096	22.9100282			
7	21.5761607	21.8421728	21.3816576	21.6346345	21.5771505	21.0008592			
8	19.916456	20.1620056	19.7369147	19.9704318	19.9173697	19.3854086			
9	18.4938521	18.7218624	18.3271351	18.5439724	18.4947004	18.0007365			
10	17.2609286	17.4737382	17.1053261	17.3077076	17.2617204	16.8006874			
11	16.1821205	16.3816296	16.0362432	16.2259759	16.1828629	15.7506444			
12	15.2302311	15.4180043	15.0929347	15.2715067	15.2309298	14.8241359			
13	14.3841072	14.5614485	14.2544384	14.4230897	14.384767	14.0005728			
14	13.6270489	13.7950565	13.5042048	13.6639797	13.627674	13.2637006			
15	12.9456964	13.1053037	12.8289946	12.9807807	12.9462903	12.6005155			

16	12.3292347	12.4812416	12.2180901	12.3626483	12.3298003	12.000491
17	11.7688149	11.9139125	11.6627223	11.8007097	11.7693548	11.4550141
18	11.2571273	11.3959163	11.1556474	11.2876354	11.2576437	10.9569701
19	10.7880803	10.9210864	10.6908288	10.8173173	10.7885753	10.5004296
20	10.3565572	10.484243	10.2631956	10.3846246	10.3570322	10.0804124
21	9.958228	10.0810028	9.8684573	9.9852159	9.9586848	9.6927043
22	9.5894047	9.7076323	9.5029589	9.6153931	9.5898447	9.3337152
23	9.246926	9.3609312	9.1635675	9.2719862	9.2473502	9.0003682
24	8.9280665	9.0381404	8.8475824	8.9522626	8.9284761	8.6900107
25	8.6304643	8.7368691	8.552663	8.6538538	8.6308602	8.4003437
26	8.3520622	8.4550346	8.2767707	8.3746972	8.3524453	8.1293649
27	8.0910603	8.1908148	8.0181216	8.1129879	8.0914314	7.8753222
28	7.8458766	7.9426083	7.7751482	7.8671398	7.8462365	7.6366761
29	7.6151155	7.7090022	7.5464674	7.6357533	7.6154649	7.412068
30	7.3975408	7.488745	7.330854	7.417589	7.3978802	7.2002946
31	7.1920536	7.2807243	7.1272192	7.2115448	7.1923835	7.0002864
32	6.9976737	7.0839479	6.9345917	7.0166382	6.9979948	6.8110895
33	6.8135244	6.8975283	6.7521024	6.8319898	6.813837	6.6318503
34	6.6388187	6.7206685	6.5789716	6.6568106	6.6391232	6.4618028
35	6.4728482	6.5526518	6.4144973	6.4903903	6.4731451	6.3002578
36	6.3149739	6.3928311	6.2580461	6.3320881	6.3152636	6.1465929
37	6.1646173	6.2406208	6.109045	6.1813241	6.1649001	6.0002455
38	6.0212541	6.0954901	5.9669742	6.0375724	6.0215304	5.8607049
39	5.8844075	5.9569562	5.8313612	5.9003549	5.8846774	5.7275071
40	5.7536429	5.8245794	5.7017754	5.7692359	5.7539068	5.6002291
41	5.6285637	5.6979581	5.5778237	5.6438177	5.6288219	5.478485
42	5.508807	5.576725	5.4591466	5.5237365	5.5090597	5.3619215
43	5.3940402	5.4605432	5.3454144	5.4086586	5.3942876	5.2502148
44	5.2839577	5.3491035	5.2363243	5.2982778	5.2842001	5.1430676
45	5.1782786	5.2421215	5.1315978	5.1923123	5.1785161	5.0402062
46	5.0767437	5.1393348	5.0309783	5.0905022	5.0769766	4.9413786
47	4.979114	5.0405014	4.9342287	4.992608	4.9793424	4.8463521

48	4.8851685	4.9453976	4.84113	4.8984078	4.8853926	4.7549115
49	4.7947024	4.8538162	4.7514795	4.8076966	4.7949223	4.6668576
50	4.707526	4.765565	4.6650889	4.7202839	4.7077419	4.5820056
51	4.623463	4.6804656	4.5817838	4.6359931	4.6236751	4.5001841
52	4.5423496	4.5983522	4.5014016	4.5546599	4.542558	4.4212335
53	4.4640332	4.5190702	4.4237912	4.4761313	4.464238	4.3450054
54	4.3883717	4.4424758	4.3488117	4.4002646	4.388573	4.2713612
55	4.3152321	4.3684346	4.2763315	4.3269269	4.3154301	4.2001718
56	4.2444906	4.2968209	4.2062277	4.2559937	4.2446853	4.1313166
57	4.1760311	4.2275173	4.1383853	4.1873486	4.1762227	4.0646824
58	4.1097449	4.1604139	4.0726967	4.1208828	4.1099334	4.0001637
59	4.0455301	4.0954074	4.0090608	4.056494	4.0457157	3.9376611
60	3.9832912	4.0324011	3.9473829	3.9940864	3.9834739	3.8770817
61	3.9229383	3.9713041	3.8875741	3.9335699	3.9231183	3.818338
62	3.864387	3.9120309	3.8295506	3.8748599	3.8645643	3.7613479
63	3.8075578	3.8545011	3.7732337	3.8178767	3.8077324	3.706034
64	3.7523758	3.7986387	3.7185491	3.7625451	3.7525479	3.6523233
65	3.6987704	3.7443725	3.665427	3.7087945	3.6989401	3.6001473
66	3.646675	3.6916348	3.6138013	3.6565579	3.6468423	3.549441
67	3.5960268	3.6403621	3.5636096	3.6057724	3.5961917	3.5001432
68	3.5467661	3.5904942	3.514793	3.5563783	3.5469288	3.452196
69	3.4988369	3.541974	3.4672958	3.5083191	3.4989974	3.4055447
70	3.4521857	3.4947476	3.4210652	3.4615415	3.4523441	3.3601375
71	3.4067622	3.4487641	3.3760512	3.4159949	3.4069185	3.3159251
72	3.3625185	3.403975	3.3322064	3.3716314	3.3626728	3.2728612
73	3.3194093	3.3603343	3.2894858	3.3284053	3.3195616	3.2309014
74	3.2773915	3.3177984	3.2478467	3.2862736	3.2775418	3.1900039
75	3.2364241	3.2763259	3.2072486	3.2451952	3.2365726	3.1501289
76	3.1964682	3.2358775	3.167653	3.205131	3.1966149	3.1112384
77	3.1574869	3.1964155	3.1290231	3.1660441	3.1576318	3.0732965
78	3.1194449	3.1579045	3.091324	3.127899	3.119588	3.0362688
79	3.0823087	3.1203104	3.0545225	3.0906621	3.0824501	3.0001227

80	3.0460462	3.0836009	3.018587	3.0543013	3.046186	2.9648272
81	3.0106271	3.047745	2.9834871	3.0187862	3.0107652	2.9303524
82	2.9760222	3.0127135	2.9491942	2.9840875	2.9761587	2.8966702
83	2.9422037	2.9784781	2.9156806	2.9501774	2.9423387	2.8637535
84	2.9091453	2.9450121	2.8829201	2.9170294	2.9092787	2.8315765
85	2.8768214	2.9122897	2.8508877	2.8846179	2.8769534	2.8001146
86	2.845208	2.8802865	2.8195592	2.8529188	2.8453385	2.7693441
87	2.8142818	2.8489791	2.7889119	2.8219088	2.8144109	2.7392425
88	2.7840207	2.8183449	2.7589236	2.7915657	2.7841484	2.7097883
89	2.7544035	2.7883625	2.7295733	2.7618682	2.7545298	2.6809607
90	2.7254098	2.7590113	2.700841	2.7327959	2.7255348	2.6527401
91	2.6970201	2.7302716	2.6727072	2.7043293	2.6971438	2.6251074
92	2.6692158	2.7021245	2.6451535	2.6764496	2.6693382	2.5980444
93	2.6419789	2.6745518	2.6181622	2.6491389	2.6421001	2.5715338
94	2.6152922	2.6475361	2.5917161	2.6223799	2.6154122	2.5455587
95	2.5891393	2.6210607	2.5657989	2.5961561	2.5892581	2.5201031
96	2.5635042	2.5951096	2.540395	2.5704516	2.5636218	2.4951516
97	2.5383718	2.5696674	2.5154891	2.5452511	2.5384883	2.4706893
98	2.5137275	2.5447192	2.4910669	2.5205399	2.5138428	2.4467021
99	2.489557	2.5202507	2.4671143	2.496304	2.4896712	2.4231761
100	2.4658469	2.4962483	2.443618	2.4725297	2.4659601	2.4000982

After adding two layers of tri-axial geogrid, table V.5 represents the values of "e"" with a 30% reduction from the original layer thickness.

e''=0.70×e





Table V.4:	Values	of "	e"	**
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	e''								
ICBR	RN 04	RN 5E	RN 11	RN 36	RN 51	RN 60			
0	42.64464701	43.17041211	42.26021737	42.76021876	42.6466033	41.50758059			
1	35.53720583	35.97534339	35.21684782	35.63351561	35.53883606	34.58965048			
2	30.46046213	30.83600863	30.18586956	30.54301341	30.46185947	29.64827187			
3	26.65290439	26.98150756	26.41263583	26.72513669	26.65412708	25.94223786			
4	23.69147053	23.98356226	23.4778985	23.75567705	23.69255742	23.05976701			
5	21.32232347	21.58520602	21.13010865	21.38010938	21.32330165	20.75379033			
6	19.38393044	19.62291457	19.20918972	19.43646306	19.38481965	18.86708208			
7	17.76860295	17.98767173	17.60842391	17.81675784	17.76941803	17.29482524			
8	16.40178729	16.60400462	16.25392972	16.44623799	16.40253972	15.9644541			
9	15.2302311	15.41800435	15.09293478	15.27150667	15.23092977	14.8241359			
10	14.21488236	14.39013737	14.0867391	14.25340623	14.21553441	13.83586022			
11	13.32645216	13.49075378	13.20631795	13.36256838	13.32706354	12.97111893			
12	12.54254323	12.69718002	12.42947566	12.57653495	12.54311863	12.20811193			
13	11.8457353	11.99178113	11.73894925	11.87783856	11.84627871	11.52988347			
14	11.22227554	11.36063474	11.12110986	11.25268914	11.22279032	10.92304752			
15	10.66116177	10.79260301	10.56505436	10.69005469	10.66165086	10.37689513			
16	10.1534874	10.27866952	10.06195652	10.18100447	10.15395318	9.88275729			
17	9.69196522	9.81145732	9.60459486	9.71823153	9.69240986	9.43354104			
18	9.27057544	9.38487221	9.18700377	9.2956997	9.27100069	9.0233871			

19	8.88430144	8.99383583	8.80421192	8.90837892	8.88470905	8.64741262
20	8.52892943	8.63408245	8.45204346	8.55204378	8.52932066	8.30151609
21	8.20089368	8.30200231	8.12696486	8.22311896	8.20126986	7.98222705
22	7.89715682	7.99452073	7.82596619	7.91855904	7.89751914	7.68658898
23	7.61511555	7.70900214	7.54646739	7.63575337	7.61546485	7.41206795
24	7.35252532	7.44317448	7.28624435	7.37245152	7.35286265	7.1564794
25	7.10744118	7.19506865	7.04336955	7.12670315	7.10776724	6.917930096
26	6.878168871	6.962969692	6.816164089	6.896809479	6.878484403	6.694771062
27	6.663226094	6.74537689	6.603158961	6.681284183	6.663531763	6.485559465
28	6.461310149	6.540971528	6.403063233	6.47882102	6.461606564	6.28902736
29	6.271271615	6.348590017	6.214737844	6.288267461	6.271559308	6.104055972
30	6.092092426	6.167201726	6.037173905	6.108602682	6.092371901	5.929654374
31	5.922867636	5.995890565	5.869474632	5.938919273	5.923139348	5.764941749
32	5.762790138	5.833839473	5.710840184	5.778407936	5.7630545	5.609132515
33	5.611137763	5.680317384	5.560554916	5.62634457	5.611395174	5.46152376
34	5.467262437	5.534668216	5.417976585	5.48207933	5.467513247	5.321484693
35	5.330580878	5.396301512	5.282527166	5.345027345	5.330825416	5.188447572
36	5.200566707	5.264684404	5.15368504	5.214660822	5.200805281	5.061900074
37	5.076743693	5.139334774	5.030978253	5.090502235	5.076976583	4.941378645
38	4.958679887	5.01981536	4.913978762	4.972118459	4.958907359	4.826462858
39	4.845982617	4.905728646	4.802297423	4.859115765	4.846204923	4.71677052
40	4.738294113	4.796712452	4.695579707	4.751135417	4.738511477	4.611953402
41	4.63528772	4.692436098	4.593501885	4.647849864	4.635500359	4.511693543
42	4.536664573	4.59259703	4.495767801	4.548959443	4.53687269	4.415700065
43	4.442150727	4.496917929	4.402105974	4.454189453	4.442354511	4.32370631
44	4.351494595	4.405144093	4.312267078	4.363287628	4.351694214	4.235467411
45	4.264464701	4.317041211	4.226021737	4.276021876	4.26466033	4.150758059
46	4.180847748	4.23239334	4.143158565	4.192178312	4.181039541	4.069370648
47	4.100446826	4.151001162	4.063482437	4.111559494	4.10063493	3.991113518
48	4.023079907	4.072680388	3.986812956	4.033982904	4.023264462	3.915809492
49	3.948578424	3.997260379	3.912983088	3.959279513	3.948759563	3.843294497
50	3.876786088	3.924582921	3.841837944	3.887292612	3.876963937	3.773416416

51	3.807557768	3.854501077	3.773233695	3.817876671	3.807732439	3.706033982
52	3.740758511	3.786878256	3.707036606	3.75089638	3.740930116	3.64101584
53	3.676262674	3.721587247	3.643122182	3.686225753	3.676431318	3.578239707
54	3.613953133	3.658509498	3.581374349	3.623747351	3.614118921	3.517591574
55	3.553720583	3.597534339	3.521684782	3.563351561	3.553883606	3.458965048
56	3.495462866	3.538558366	3.46395224	3.504935966	3.495623222	3.402260701
57	3.439084439	3.481484846	3.408082041	3.448404736	3.439242205	3.347385531
58	3.384495793	3.426223185	3.353985502	3.393668152	3.384651053	3.29425243
59	3.331613047	3.372688445	3.301579477	3.340642088	3.331765885	3.242779736
60	3.280357465	3.320800931	3.250785951	3.289247598	3.280507944	3.192890813
61	3.230655078	3.270485764	3.20153162	3.23941051	3.230803282	3.14451368
62	3.182436341	3.221672545	3.153747562	3.191061104	3.182582333	3.09758064
63	3.135635811	3.174295005	3.107368922	3.144133734	3.135779654	3.052027986
64	3.090191811	3.128290732	3.06233459	3.098566576	3.090333575	3.007795693
65	3.046046213	3.083600863	3.018586956	3.054301341	3.046185947	2.964827187
66	3.003144158	3.040169867	2.976071644	3.011283009	3.003281925	2.923069058
67	2.961433818	2.997945286	2.934737316	2.969459633	2.961569674	2.882470878
68	2.920866235	2.956877539	2.894535434	2.928782108	2.921000229	2.84298497
69	2.881395069	2.916919733	2.855420092	2.889203968	2.88152725	2.804566254
70	2.842976465	2.878027474	2.81734782	2.850681253	2.843106889	2.767172037
71	2.805568885	2.840158692	2.780277458	2.813172285	2.805697587	2.73076188
72	2.769132919	2.803273515	2.74416996	2.776637584	2.769259955	2.695297444
73	2.733631215	2.767334108	2.708988289	2.741039665	2.73375662	2.660742343
74	2.69902829	2.732304561	2.674697298	2.706342961	2.699152106	2.62706206
75	2.665290439	2.698150756	2.641263583	2.672513669	2.665412708	2.594223786
76	2.632385616	2.664840255	2.608655392	2.639519673	2.63250638	2.562196336
77	2.600283357	2.632342202	2.57684252	2.607330411	2.600402644	2.530950037
78	2.56895464	2.600627232	2.545796225	2.575916791	2.569072485	2.500456665
79	2.538371843	2.569667387	2.51548913	2.545251114	2.538488295	2.470689319
80	2.508508646	2.539436004	2.485895139	2.515306983	2.508623726	2.441622386
81	2.47933994	2.50990768	2.456989381	2.486059233	2.479453683	2.413231429
82	2.450841785	2.481058167	2.428748126	2.457483833	2.450954212	2.385493138

83	2.422991305	2.452864323	2.401148715	2.429557886	2.423102458	2.35838526
84	2.395766688	2.425304049	2.374169511	2.402259482	2.395876588	2.33188655
85	2.369147053	2.398356226	2.34778985	2.375567705	2.369255742	2.305976701
86	2.343112471	2.372000666	2.321989964	2.34946257	2.343219963	2.280636295
87	2.31764386	2.346218049	2.296750946	2.323924932	2.317750183	2.255846768
88	2.292722957	2.320989895	2.272054694	2.298936493	2.292828132	2.231590354
89	2.26833229	2.296298515	2.247883904	2.274479718	2.268436345	2.207850029
90	2.244455108	2.272126955	2.224221965	2.250537828	2.244558071	2.184609504
91	2.221075367	2.248458961	2.201052987	2.22709473	2.221177252	2.161853155
92	2.198177681	2.225278972	2.178361717	2.204134989	2.198278523	2.139566009
93	2.175747294	2.202572043	2.156133539	2.181643814	2.175847107	2.117733702
94	2.153770052	2.180323845	2.134354411	2.159607009	2.153868857	2.096342451
95	2.132232347	2.158520602	2.113010865	2.138010938	2.132330165	2.075379033
96	2.111121138	2.137149112	2.092089965	2.116842511	2.111217983	2.054830722
97	2.090423874	2.11619667	2.071579279	2.096089156	2.090519767	2.034685324
98	2.070128494	2.095651075	2.051466865	2.075738777	2.070223463	2.0149311
99	2.050223413	2.075500581	2.031741222	2.055779747	2.050317465	1.995556759
100	2.030697473	2.055733911	2.012391304	2.036200894	2.030790636	1.976551458

V.6.Conclusion:

A distinct disparity is observed among the values of 'e', " e' ", and " e'' ". When one or two layers of geogrids are incorporated, the thickness of the pavement decreases.

CHAPTER VI NUMERICAL ANALYSIS

NUMERICAL ANALYSIS

VI.1.Preamble:

In order to compare the results of the two calculations: using artificial neural networks (ANN), established by applying the "Python" software, and those using the finite element method (FEM), this chapter has been written to present the numerical analysis using FEM and to give an overview of the software applied and the methodology adopted for modeling linear pavements with and without geogrid reinforcement.

VI.2.Problematic:

As discussed in the bibliography, the design of a linear pavement (road or airport) is always influenced by several parameters. According to the design codes and standards, these parameters are the type of loading, the intensity of the traffic, the physical bearing capacity of the subgrade (ICBR), the thickness of the wearing courses (surface concrete and asphalt gravel), as well as the possible insertion of layers of geogrids [47].

VI.3.Introduction to the Finite Element Method:

Numerical analysis is a branch of mathematics, applied mathematics, whose aim is to develop and study methods of numerical resolution, in order to solve numerically equations that are derived from problems posed by physics or the applied sciences [48]. In civil engineering, this analysis consists in falling a calculation model, not far from the real example (structure, building, bridge, dam) and capable of solving the complex problem found in practice. Its purpose is to validate the results obtained from an experimental study, analytical analysis or manual calculation [49].

In this chapter we will present various models, using the finite element method (MEF), concerning the pavement layer, before and after geogrid reinforcement. This will be done using the Ansys commercial software (Worbench version). Our work will consist of three modeling phases. The first phase involves a pavement without reinforcement. The second phase includes a pavement reinforced with one layer of geogrid. Lastly, the third phase comprises a pavement reinforced with two layers of geogrid for all the projects mentioned in the previous chapter.
VI.4.Calculation software and details:

In civil engineering, it is generally required to make a good choice for the work tool (software), for any numerical analysis, in order to get closer to reality, finding a suitable model and minimizing the gap between experimental and numerical results. In the world of computer programs, there is a lot of software, based on the finite element method, dealing with the resolution of partial differential equations for the determination of the stiffness matrix and therefore the determination of stresses and strains at any node (point) of the modelled element.

Among these programs, we mention 'ANSYS', which is a multidisciplinary simulation software based on the finite element method that offers many analytical possibilities such as static, dynamic, linear and non-linear analysis. linearity, ANSYS is able to take into account the plasticity, the great deformation, the hyper-plasticity, the shrinkage and the anisotropy of the materials, and the most important is that ANSYS takes into account the behaviour of the cracked concrete and the interaction between the different materials which makes it the most relevant choice for our study [50].

Engineer John A. Swanson developed the Ansys software in 1970 and since then more than 90 products for different applications have been developed, including:

- ANSYS Structural;
- ANSYS Mechanical;
- ANSYS CFX and Fluent;
- ANSYS AUTODYN and ANSYS LS-DYNA
- ANSYS Gambit;
- ANSYS Electromagnetics and Ansoft;
- ANSYS Multiphysics;

The implementation of the ANSYS code can take place in two different software environments depending on the complexity of the geometry and the user experience:

VI.4.1.ANSYS Classic:

A solution intended for users competent in the field of numerical simulation for the construction of finite element models with simple geometry constructable using basic operations. The model is built directly using the ANSYS Parametric Design Language (APDL).





VI.4.1.ANSYS Workbench:

This approach is rather suitable for processing complex geometries and users less experienced in the field of calculation. The work in this environment is done mainly on a geometry and no longer on a model, and the platform then converts the input requests into ANSYS code. In addition to its speed and efficiency, the APDL offers the following advantages compared to the Workbench:

- Direct entry of orders or functions to be performed;
- Import / create geometries as required to create the model;
- Attribute elements, materials and create effective and efficient mesh;
- Contact management, complex interactions and linkage between different model regions;

Modélisation Ouadah - Workbench Reher Afficher Oudis Unités Extensions La La L	Täches Alde rojet 🍠 Mettre ä jour le projet 🎢 Mettre ä jour to	uai les points de calcul 🛛 🧱 Piege de démarrage ACT				- a x	
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El Systèmes d'analyse							
Acoustigue harmonique							
Acoustique modal	▼ A	• B	• C	• D	• E	• F	
Acoustique statique	1 📅 Shuture statique	1 📴 Stucture statique	1 🐻 Structure statique	1 Structure statique	1 🐻 Structure statique	1 Shucture statique	
g Calcul méridien	2 🔮 Données techniques 🗸 🚽	2 🖉 Données techniques 🧹	2 🔮 Données techniques 🗸 🗸	2 g Données techniques 🗸	2 🜒 Données techniques 🧹	🗕 2 🦪 Dannées techniques 🗸	
Calcul méridien (BladeGen)	3 🖸 Géométrie	3 🖸 Géorrétrie	3 Géométrie	3 Gioreltrie	3 Giomitie	3 D Giositrie	
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12 Dynamique explicite	5 gg compand V	3 gg compoiedon	o gg cungu doon	3 gg compadoon	3 (gg congu add)	5 gg congrand	
Cynamique rigide	6 📷 Solution 🗸	6 💽 Solution 🗸	6 y Solution 🗸	6 👹 Solution 🗸	6 🚛 Solution	6 🛄 Solution	
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U Electrique	RC Beam (Ref)	→ 8 🛱 Paramètres	-> 8 D Paramètres	> 8 🛱 Paramètres	> 8 1pJ Paramètres	-> 8 🛱 Paramètres	
Consumer (Pelyflew) Fandage Initiaries Telandage Initiaries Le Schwa Le Sch		RC Beam + CFSP	RC Beam + CFRP + 8.5% CMTs	RC Beam + GYRP + 8.2% CMTs	RC Beam + O'RP + 0.3% Off's	RC Beam + CTRP + 8.4% Off's	
1 Thermoélectrique		Ensemble de paramètres					
Transitoire en champ couplé							
Vibration aléatoire							
te systemes de composants							
w systemes personnalisés							
El Exploration de la conception El ACT							
Tout afficher / Personnaliser					Suivi des tâches	Afficher la progression 44 Afficher 14 messages	

Figure VI.2: Ansys GUI Workbench

VI.5.Methodology and modeling stages:

The modeling work consists of taking real case studies to calculate (predict) the values of stresses and strains (or displacements), under linear loading of the heavy goods vehicle load P, over a length of 1m. The parameters for the calculation are: the load P, the dimensions of the pavement in "3D", the type of soil (ICBR value), the mechanical characteristics of the surface layers of the pavement body (asphalt concrete/AC and bituminous gravel/BG), the average thickness of the pavement (determined by the prediction of the calculation using neural networks (ANNs)). We have taken 6 example cases, relating to the real study cases taken in our previous calculations. As shown in the table below (Table VI.5), we took the case of the unreinforced pavement, the case of the pavement reinforced with one layer of geogrid and the case of the pavement reinforced with two (02) layers of geogrid. Figures VI.3, VI.4 and VI.5 show the modelling cases considered.

Case	Type of soil	ICBR	Load P (tonne)	Thicknesse e (cm)	Young's modulus E (MPa)	Poisson coefficient
1	Very poor	Between 0 and 20	6.5	65	1500	0.20
2	Poor	Between 21 and 40	6.5	55	2400	0.20
3	Poor/Average	Between 41 and 55	6.5	40	3000	0.25
4	Fairly good	Between 56 and 65	6.5	30	4500	0.25
5	Good	Between 66 and 79	6.5	20	5800	0.25
6	Very good	Between 80 and 100	6.5	10	7000	0.25
-	Geogrid	-	-	0.3	800	0.30

The three modeling cases are illustrated as follows:

• 1st case: Unreinforced carriageway (Dimensions: 1m*1m*e)



Figure VI.3: The case of an unreinforced pavement

• 2nd case: Pavement reinforced with 1 geogrid layer (between AC and BG)



Figure VI.4: Pavement reinforced with 1 layer of geogrid

• 3rd Case: Pavement reinforced with 2 geogrid layers (between AC and BG) and under the BG _____



Figure VI.5: Pavement reinforced with 2 layers of geogrid

VI.6.Models chosen for the case studies:

Numerical analysis for the studied cases allowed us to define the selected models using the "Ansys Workbench" software. These cases include six (06) different types of soils, namely the unreinforced pavement, the pavement reinforced with one layer of geogrid, and the pavement reinforced with two layers of geogrids (Figures VI.5, VI.6, and VI.7).



Figure VI.6: Model for unreinforced pavement



Figure VI.7: Model for reinforced pavement with 1 geogrid layer



Figure VI.8: Model for reinforced pavement with 2 geogrid layers

The results of the stresses and displacements found for the various cases studied will be discussed in the next chapter (Chapter VII).

CHAPTER VII

Comparative results and discussion

COMPARATIVE RESULTS AND DISCUSSION

VII.1.Introduction:

This final chapter of the thesis focuses on the presentation of results and the subsequent commentary on the findings obtained from the study on the application of artificial neural networks to predict the behaviour of linear pavement using Python programming language. This research aimed to develop an effective model that can accurately predict the performance of pavement based on various factors. a dataset was employed comprising relevant pavement attributes and applied advanced machine learning techniques to train our neural network model. In the previous chapters, we outlined the methodology employed and described the data collection process, Python library and tools, and Reinforcing with geogrids, in this section, we discuss the outcomes of our model training, the results obtained from the comparison of pavements before and after reinforcements, and provide insightful comments on the implications of our findings.

VII.2.Results of applying neural networks:

The dataset used in this study consisted of three main factors (P, N, ICBR), which were applied based on the relationship of 'e'. The obtained curves represent the difference in thickness between each layer of the pavement before and after reinforcement with geogrids.

Despite manual or empirical calculations, which are too tiring, and due to the lack of methods and theories giving rise to the precision of the values found for pavement thickness as a function of soil type and traffic intensity, the work carried out, through the application of neural networks, has enabled us to estimate the exact value of thickness in different cases and subgrade soil (value of the CBR index). The figure opposite (Figure VII.1), shows the superposition of the thickness values (e) found in cm, as a function of the value of the ICBR.



Figure VII.1:Superimposed curves in the Python application

As the curves depict, there is a noticeable difference between 'e', 'e'', and 'e"'. The thickness of the pavement decreases when one or two layers of geogrids are added. To conclude, the addition of geogrid layers consistently results in reduced pavement thickness." In conclusion, this study successfully applied artificial neural networks to predict the behavior of linear pavement using the Python programming language. The results reveal the relationship between the different values of ICBR and their effect on the pavement thickness with geogrid reinforcement. The findings of this study contribute to the field of pavement engineering and highlight the potential benefits of employing artificial neural networks in predicting the behavior of linear pavement.

VII.3.ANSYS application results:

The objective of the finite element (FE) modelling, using Ansys-Worbench software, was to determine the stresses and displacements of the geogrid-reinforced or non-geogrid-reinforced pavement. Once the thicknesses of the two surface layers (AC and BG) of the pavement were known, following prediction by neural networks (using Python) and with the

introduction of mechanical and geometric characteristics, the figures below illustrate the states of stresses and displacements. A summary table of the values found is presented at the end.

VII.3.1.Stress values:

The worst case is taken for the average CBR index, which varies between 41 and 55. Figures VII.2 (a), VII.2 (b) and VII.2 (c) illustrate the stress states for the case of no reinforcement, reinforcement with one layer of geogrid and reinforcement with two layers of geogrid.



Figure VII.2(a):Unreinforced pavement Figure VII.2(b):Pavement reinforced with 1



layer

Figure VII.2(c) : **Pavement reinforced with 2 layers**

VII.3.2.Displacement values:

For the average CBR index which varies between 41 and 55 (poor soil). Figures VII.3 (a), VII.3 (b) and VII.3 (c) illustrate the states of displacement for the case without reinforcement, reinforcement with one layer of geogrid and reinforcement with two layers of geogrid.









Figure VII.3(c): Displacement for 2 layers of reinforcement

For all the studied cases, the following table (Table VII.1) summarizes the values of stresses and displacements, as well as the differences found compared to the unreinforced pavement.

Type of soil		Very poor	Poor	Poor/Average	Fairly good	Good	Very good
Thicknesse e (cm)	v arues/ Kesuits	65	55	40	30	20	10
No reinforcement	Stress (MPa)	4.102	2.774	4.178	4.206	7.099.	8.885
	Displacement (mm)	0.0014	0.0044	0.00107	0.00072	0.0048	0.0074
Reinforcement with 1 geogrid layer	Stress (MPa)	2.415	2.8244	4.2243	5.7593	7.7492	11.032
	Displacement (mm)	0.0029	0.00264	0.00147	0.00175	0.004078	0.01039
Reinforcement with 2 geogrid layers	Stress (MPa)	2.343	2.7452	4.1024	5.5733	7.3935	13.032
	Displacement (mm)	0.0029	0.00259	0.00137	0.00167	0.00314	0.01377
Comparison (difference) (%)	Stress (MPa)	-42.88	-1.04	-1.809	32.51	4.15	46.67
	Displacement (mm)	107.14	-41.14	28.04	131.94	-34.58	86.08

Table VII.1:Comparative table of results obtained

A comparison was made between the values for the unreinforced layer and the worst case (reinforcement with two layers of geogrid) for the different soil types. On the basis of the comparisons, it can be said that reinforcement has a positive influence on stress values (gain of up to 47%) and displacements (gain of up to 132%) for good quality soils. In the case of low bearing capacity soils, geogrids have little effect, as the thickness of the pavement overlay is greater.

General Conclusion and Recommandations

General Conclusion and Recommandations

At the end of this study, the initial aim was to understand linear pavements, geosynthetics and artificial neural networks (ANNs), with the prediction of the behaviour of linear pavements over time using artificial intelligence through a method called neural networks. After several attempts to understand and program the neural networks using Python software, based on a database of more than 600 case studies, six cases of soil types, in different regions of Algeria, characterised by different types of climate and heavy traffic, we were able to predict the behaviour of these structures using ANNs by determining the thickness of overlay required (e) as a function of the intensity of traffic, the bearing capacity of the soil (CBR) and the value of the load applied (heavy lorry).

Once the thickness was known, the finite element (FE) method was used to determine the behaviour of the pavement using Ansys/Worbench software. This modelling of the case studies enabled us to determine stress and displacement values with gains of up to 47% for geogrid reinforcement (for stresses) and gains of up to 132% for displacements.

However, to further optimise these variances, it is recommended that future studies increase the number of case studies (broaden the database), explore more specialised research in this area, and conduct more experimental tests to improve programming using appropriate neural network software (such as Matlab or Pytho) and FE analysis software such as Ansys, Abaqus or others. **Bibliographical references**

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