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GROUND VIBRATION ISOLATION USING ARTIFICIAL NEURAL NETWORK

By:

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ABSTRACT

Ground vibration is a growing concern in urban areas due to increased construction activities and infrastructural development. Common sources include pile driving, heavy equipments, road and train traffics. Due to land shortage in urban areas, buildings and other structures are often situated near source of vibrations. This proximity has potential of causing structural damage and discomfort to nearby residents. These vibrations can be mitigated by controlling the source, inserting wave barrier in the transmission medium (soil), or isolating the base of the target building or structure. However, using trenches as wave barrier are most practical because of their low-cost, rapidity and simplicity.

Several studies were conducted on the use of trenches for vibration screening. It was demonstrated that trenches are very efficient for screening vibrations. This thesis presents the use of Artificial Neural Network (ANN) for ground vibration isolation. An open trench was employed as a wave barrier for mitigating ground vibration.

A 3D finite Element (FE) model was developed using COMSOL Multiphysics. The model was first studied in the absence of trench. It was later studied with an open trench in the propagating path. These studies were done for nine soils with distinct soil parameters such as young modulus, Poisson ratio and density. A database was generated composing soil parameters and trench parameters.

A Neural network was created using MATLAB. Levenberg-Marquardt Algorithm was used to train the neural network. Input includes soil young modulus, Poisson ratio, soil density, trench width, trench depth and trench length. Output was the amplitude reduction ratio (Ar) i.e., ratio of peak acceleration with trench to peak acceleration without trench. Datasets of six soils was used for training while three datasets were used for testing the neural network. A different dataset was used for making predictions.

According to predicted output, the highest isolation level achieved is 68.28%and this requires a trench which is 1.5m wide, 10m deep and 17.5m long.

Keywords:

Artificial Neural Network, ground vibration, open trench, vibration isolation, vibration screening.

RESUME

Les vibrations du sol sont une préoccupation croissante dans les zones urbaines en raison de l'augmentation des activités de construction et du développement des infrastructures. Les sources courantes comprennent le battage de pieux, les équipements lourds, la circulation routière et ferroviaire. En raison de la pénurie de terrains dans les zones urbaines, les bâtiments et autres structures sont souvent situés à proximité de sources de vibrations. Cette proximité peut causer des dommages structurels et un inconfort pour les résidents voisins. Ces vibrations peuvent être atténuées en contrôlant la source, en insérant une barrière d'ondes dans le milieu de transmission (le sol) ou en isolant la base du bâtiment ou de la structure cible. Cependant, l'utilisation de tranchées comme barrière d'ondes est la plus pratique en raison de leur faible coût, de leur rapidité et de leur simplicité.

Plusieurs études ont été menées sur l'utilisation de tranchées pour l’isolation des vibrations. Il a été démontré que les tranchées sont très efficaces pour filtrer les vibrations. Cette thèse présente l'utilisation d'un réseau de neurones artificiels (RNA) pour l'isolation des vibrations du sol. Une tranchée ouverte a été utilisée comme barrière d'ondes pour atténuer les vibrations du sol.

Un modèle éléments finis en 3D a été développé à l'aide de COMSOL Multiphysics. Le modèle a d'abord été étudié en l'absence de tranchée, puis avec une tranchée ouverte sur le trajet de propagation. Ces études ont été réalisées pour neuf types de sols présentant des paramètres distincts tels que le module de Young, le coefficient de Poisson et la densité. Une base de données a été générée regroupant les paramètres des sols et des tranchées.

Un réseau de neurones a été créé à l'aide de MATLAB. L'algorithme de Levenberg-Marquardt a été utilisé pour entraîner le réseau de neurones. Les données d'entrée comprennent le module de Young du sol, le coefficient de Poisson, la densité du sol, la largeur de la tranchée, la profondeur de la tranchée et la longueur de la tranchée. La sortie était le taux de réduction d'amplitude (Ar), c'est-à-dire le rapport de l'accélération maximale avec tranchée à l'accélération maximale sans tranchée. Des ensembles de données de six sols ont été utilisés pour l'entraînement, tandis que trois ensembles de données ont été utilisés pour tester le réseau de neurones.Un nouvel ensemble de données a été utilisé pour faire des prédictions.

D'après les prévisions, le taux d'isolation le plus élevé atteint est de 68,28%, ce qui nécessite une tranchée de 1,5 m de large, 10 m de profondeur et 17,5 m de long.

ملخص

تعد اهتزازات التربة مصدرقلقمتزايدفيالمناطقالحضريةبسببزيادةأنشطةتطوير البناءوالبنيةالتحتية . تشملالمصادر الشائعةحركة طرقوالسكك الحديدية والمعدات الثقيلة.نظرًالندرةالأراضيفيالمناطقالحضريةوالمبانيوغيرها من الهياكلالأخريغالبا ما تكونبالقربمنمصادرالاهتزاز .هذاالقربيمكن ان يسببأضرارهيكليةوازعاج المقيمين المجاورين . يمكنتهياكهذهالاهتزازاتمنخلالالتحكمفيالمصدر ،أوإدخالحاجزالموجةفيوسيلةالنقل (التربة)،أوعزلقاعدةالمبنىأوالهيكلالمستهدف .ومعذلك،فإناستخدامالخنادق بمثابةحاجزالموجةهوالأكثرعمليةبسببتكلفتهاالمنخفضةوسرعتهاوبساطتها.

أجريت عدةدراساتحولاستخدامالخنادقلفحصالاهتزازةتمإثباتفعاليةالحفربشكلكبيرفيفحصالاهتزازات . تقدمهذهالأطروحةاستخدامالشبكاتالعصبيةالاصطناعية (ANN) لعزلالاهتزازاتالارضية . تماستخدامخندقمفتوحكحاجزموجةلتخفيفالاهتزازاتالارضية.

تمتطويرنموذجعنصرثابتثلاثيالأبعاد (FE)باستخدامCOMSOLMultiphysics .تمتدراسةالنموذج لأول مرة فيغياب الخنق،ثمتمتدراستهبوجودحفرةمفتوحةعلىمسارالانتشار .تمإجراءهذهالدراساتلتسعةأنواعمع معلمات تربة متميزة. تم انشاء قاعدة البيانات لتأليف معلمات التربة والخنادق.

يتم انشاء شبكة عصبية باستخدام Matlab. يتم استخدام خوارزمية Levenberg-Marquardt لتدريب الشبكة العصبية. تتضمن بيانات الادخال وحدة Young للتربة ومعامل Poisson وكثافة التربة وعرض وعمق وطول الخندق.

كان إخراج معدل تخفيض السعة (CA) أي ان نسبة التسارع القصوى مع خندق مع نسبة التسارع القصوى بدون خندق. تم استخدام ست مجموعات من بيانات للتربة للتدريب في حين تم استخدام ثلاث مجموعات من البيانات لاختبار الشبكة العصبية. تم استخدام مجموعة من بيانات جديدة للتنبؤ.

وفقا للتوقعات تم الحصول على اقصى عزل بنسبة 68.28% والذي يتطلب خندق من 1.5 متر عرضو10 أمتار عمق وطول 17.5 متر.

ACKNOWLEDGEMENTS

Foremost, I thank Allah Almighty for guiding me throughout this academic journey and completion of this thesis. Without His blessings and mercy, I would not have been able to achieve this milestone.

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I would like to express my deepest gratitude to my parents for their unconditional love, constant support throughout my educational journey. Their encouragement and prayers have been my driving force, enabling me to pursue my dreams and accomplish this significant milestone.

The acknowledgement won't be complete without expressing my sincere appreciation to my great country Nigeria for the wonderful opportunity through the Federal Scholarship Board to pursue my Engineering Ambition. God bless the Federal Republic of Nigeria.

Lastly, I would like to acknowledge the contributions of all the individuals who directly or indirectly assisted me in completing this thesis. Their assistance and valuable insights played a crucial role in enhancing the quality of this work.

I am sincerely grateful to everyone mentioned above for their immense contributions and unwavering support, without which the completion of this thesis would not have been possible. May Allah bless you all abundantly.

DEDICATION

I dedicate this beautiful work to:

My dear father: For his support and prayers

My lovely Mum: To whom I’m indebted

My brothers and sisters

My Academic Mentor: Engineer Yakubu Khartum

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CHAPTER I GENERAL INTRODUCTION

I.1. Introduction

Construction activities and industrializationin urban areas and megacities largely generate ground vibrations. Notable sources of ground vibrations include train induced, road induced vibration, pile driving and blasts from mines. Due to land shortage in these urban areas, constructions/structures are often built near these vibration sources. Thesevibrations are propagated in form of elasticwaves through the soil media to the surroundingsand can affect adjacent structures.High intensity vibrations may cause serious damage to structures/buildings. Damages caused by vibration can vary from minor architectural damages to existing structures to severe structural failure. Apart from the potential of structural damages, these vibrations can be annoying because they disturb activities in structures/building as well as causing discomfort to the occupants.

Since controlling vibration is notfeasible and the use of base isolators can be very costly, installing wave barriers in the propagation path of waves to screen vibrations is a better choice. These waves barriers could be in form of open trenches, infilled trenches, sheet-pile walls, rows of solid or hollow concrete or steel piles, andgas-cushion screen system. Use of trenches is the most common and practical means of ground vibration isolation. Trenches are commonly used because of their effectiveness in vibration screening, its simplicity and low cost of installation.

An open trench is suitable for vibration screening in areas where soil instability is not an issue otherwise an in-filled trench can be constructed.Open trench is more efficient in vibration screening because there is no energy transfer through the air. Whereas vibration screening occurs in in-filled trench when the propagating wave encounter an in-filled material whose impedance value is different from that of the surrounding soil. Trenches can be installed for achieving an active isolation (installing the barrier or trench close to the vibration source) or passive isolation (installing the barrier or trench a far distance from the vibration source). Active isolation systems can be effectively used in the case of dynamically loaded foundations (machine foundations, where the barrier needs to be installed close to the foundation) while passive isolation systems are suitable for protecting residential areas against the induced vibration due to the passing of high-speed trains.

Ground vibrations induced by machine foundations (rotating machines) are steady-state and are described as periodic, low to high-frequency, and low-amplitude excitations while ground vibrations originating from traffic activities, such as high-speed trains are transient with a significantly low-frequency. Most of these vibrations are propagated in the soil in the form of surface waves and can travel for long distances. A machine foundation on the ground surface would generate both body waves that radiate in all directions and surface waves in the form of Rayleigh waves (R-waves), which propagate horizontally in a zone close to the free ground surface. The R-waves carries most of the dynamic energy emitted into the ground. Also, body waves have a much higher radiation damping compared to R-waves. Therefore, in terms of prominent waves versus the system efficiency: for active vibration and because the barrier is constructed close to the source of disturbance, not only do body waves dominate the system protective efficiency, but body waves also dominate and influence the system behaviour. For passive isolation, the wave field along the ground surface and far from the source of disturbance is determined almost by the R-wave alone (Alzawi, 2011).

I.2. Aim and Objectives

The main aim is to develop a design method for trench configuration for achieving different levels of isolation in open trenches using an Artificial Neural Network. The trench dimension (width, depth and depth) would determine the level of vibration isolation that can be achieved.

I.3. Thesis outline

This thesis is composed of six chapters as follows:

Chapter 1 presents a general introduction on ground vibration and its isolation and then followed by aim and objectives of the thesis.

Chapter 2 begins with a comprehensive literature review of wave propagation through soil media and common vibration sources. Vibration isolation methods are discussed, with use of trenches highlighted as a more feasible and practical approach to screen ground vibration.

Chapter 3 presents a 3D numerical study using finite element modelling. COMSOL Multiphysics was used for modelling the soil media, trench and prescribing excitation in FE model. Database was generated from this study and was used to feed the Artificial Neural Network.

Chapter 4 focuses developing an Artificial Neural Network for predicting the acceleration amplitude reduction ratio. In this chapter, ANN was first trained, tested and then predictions were made using the trained network. The database generated in chapter 3 was used as inputs and outputs parameters for the ANN model.

Chapter 5comprises discussions and analysis the results gotten from the ANN. A table is presented showing the trench dimensions for achieving some levels of isolation.

Chapter 6 present conclusions based on this thesis

CHAPTER II: LITERATURE REVIEW

II.2 Introduction

Vibration is the motion of a particle or a body or a system of connected bodies displaced from a position of equilibrium. Most vibrations are undesired in machines and structures because they produce increased stresses, energy losses, cause added wear, increase bearing loads, induce fatigue, create passenger discomfort in vehicles, and absorb energy from the system.

Vibration occurs when a system is displaced from a position of stable equilibrium. The system tends to return to this equilibrium position under the action of restoring forces (such as elastic forces, in mass attached to a spring, or gravitational forces, in a simple pendulum). The system keeps moving back and forth across its position of equilibrium.(Rao and Srinivas, 2012).

II.3. Vibration terminologies

Period - is the time required for one complete cycle of oscillation. The S.I unit of period is in seconds (s)

Frequency- is the number of cycles of oscillation per second. The S.I unit of frequency is in Hertz(Hz)

Amplitude:is the maximum displacement of a vibrating particle or body from its position of rest.It is expressed in metrics (mm,cm)

Resonance - is a phenomenon that amplifies a vibration. It occurs when a vibration is transmitted to another object whose natural frequency is the same or very close to that of thesource(Erbessd, 2019).

Peak particle velocity- is the maximum resultant particle velocity Vr (max) characterizes the vibration severity. It is expressed in m/s.(Technical Note 03, 2013)

II.4. Soil vibration propagation

A ground that has a free surface is often idealised simply as a half-space (or semi-infinite domain) of homogeneous and isotropic elastic material. At the free surface of a half-space, interaction between dilatational and shear waves results in a surface wave or 'Rayleigh' wave (Rayleigh, 1885).

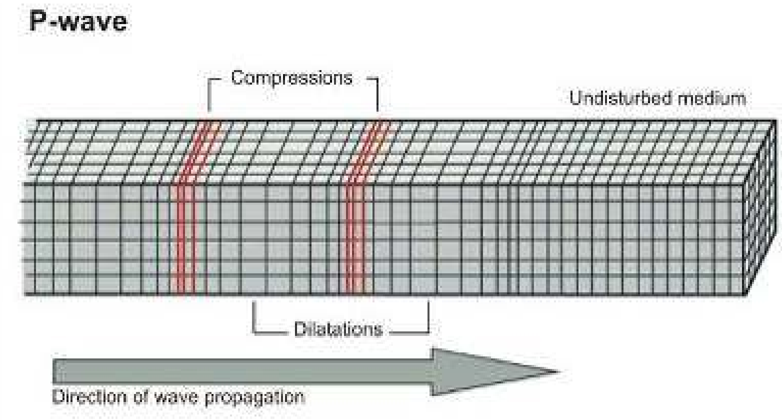
It is the Rayleigh wave that usually carries the greatest part of the wave energy that is transmitted, particularly to larger distances along the surface. However, all grounds are stratified on some scale and this layered structure of the ground has important effects on the propagation of surface vibration in the frequency range of interest. Typically, grounds have a layer of softer weatheredmaterial that is only about 1–3 m deep on top of stiffer soil layers or bedrock, depending on the geology of each site. In such a layered ground medium, vibration propagates parallel to the surface via a number of wave types or 'modes'. These are often called Rayleigh waves of different orders ('R-waves') and Love waves. The Rayleigh waves are also called P-SV waves since they involve coupled components of dilatational deformation and vertically polarised shear deformation. Here the name P-SV wave is preferred and the term Rayleigh wave is reserved for the single such wave that exists in a homogeneous half-space. Love waves are decoupled from these and only involve horizontally polarised shear deformation and so are also known as SH waves. Since the vertical forces in the track dominate the excitation of vibration in the ground, the SH waves are not strongly excited and usually are ignored in the calculations of ground vibration from railways.

• Compression or p-waves are body waves that expand from the energy source along a spherical wave front. The particle motion is along the direction of expanding wave front in a "push-pull" manner.

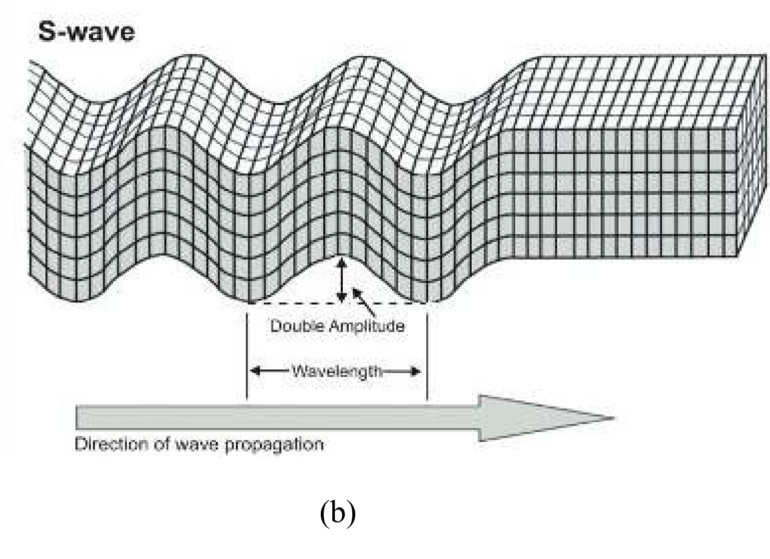
• Shear or s-waves are also body waves expanding along a spherical wave front. However, particle motion is perpendicular (transverse) to the direction of wave propagation.

• Surface or Rayleigh waves travel along the ground surface. These waves expand along a cylindrical wave front, analogous to ripples formed by dropping a pebble into a body of water. The particle motion is a retrograde ellipse in a vertical plane resulting in motion both along and perpendicular to the direction of wave propagation. Rayleigh wave motion penetrates the ground surface by a distance of only one to two wavelengths.(Jackson et al., 2008)

Rayleigh waves, compression (primary) waves and shear(secondary) wavesare mainly responsible for transmission of vibratory energy from a source to near or far distance.At small distances from the vibration source, all three wave types will arrive together and greatly complicate wave identification; whereas at large distances, the more slowly moving S- and R-waves begin to separate from the P-wave and allow identification. The P-, S- and R- waves travel at different speeds. The P-wave is the fastest, followed by the S-wave, then the R-wave(Czech, 2016).



(a)



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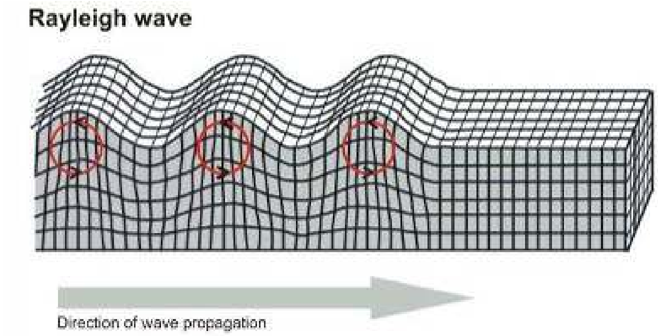

(c)

Fig 2.1. Displacement characteristics of waves (a) P wave (b) S wave (c) Rayleigh waves

(Namet al., 2013)

II.5. Sources of ground vibrations

II.5.1 Road/Traffic induced vibrations

When a bus or a truck strikes an irregularity in the road surface, it generates an impact load and an oscillating load due to the subsequent "axle hop" of the vehicle. The impact load generates ground vibrations that are predominant at the natural vibration frequencies of the soil whereas the axle hop generates vibrations at the hop frequency (a characteristic of the vehicle's suspension system). If the natural frequencies of the soil coincide with any of the natural frequencies of the building structure or its components, resonance occurs and vibrations will be amplified.(Hunaidi, 2000)

According toHunaidi (2000), Road traffic tends to produce vibrations with frequencies predominantly in the range from 5 to 25 Hz (oscillations per second). The amplitude of the vibrations ranges between 0.005 and 2 m/s^2(0.0005 and 0.2 g) measured as acceleration, or 0.05 and 25 mm/s measured as velocity. The predominant frequencies and amplitude of the vibration depend on many factors including the condition of the road; vehicle weight, speed and suspension system; soil type and stratification; season of the year; distance from the road; and type of building. The effects of these factors are interdependent and it is difficult to specify simple relation- ships between them.

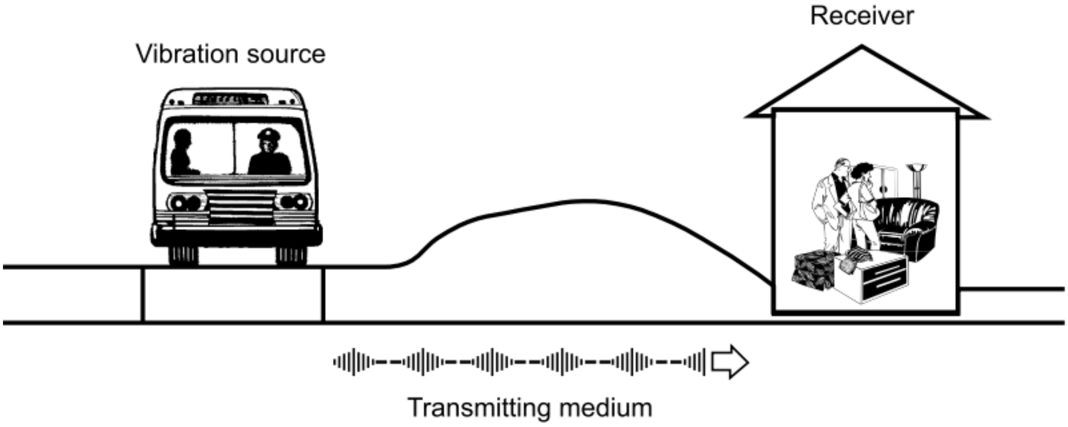

Fig 2.2: Road/Traffic induced vibrations (Hunaidi, 2000)

II.5.1. Train induced vibrations

The movement of trains on a railway track causes the emission of vibrations that are transmitted by the ground at fairly large distances.

The origin of these vibrations is multiple:

- Successions of rolling loads,

- wheel/rail sliding phenomena,

- Imperfections in the geometry of the wheel and rail.

They can be classified into three frequency bands:

- From 0 to 15 Hz: mainly due to the suspended masses of the vehicles, which are fairly well transmitted by the ground and constitute the proper field of vibrations.
- From 15 to 150 Hz: these vibrations are mainly the result of oscillations of non-suspended masses. They are already significantly weakened by the ground but can be very annoying because the vibrations of structures they generate (walls, ceilings) produce very perceptible noises.
- Above 150 Hz: it is mainly the phenomena of wheel/rail sliding that cause them. They are very quickly cushioned by the ground, but on the other hand they produce, through the rail and the wheel as a radiant surface, what is called: rolling noise(Alias J, 1984).

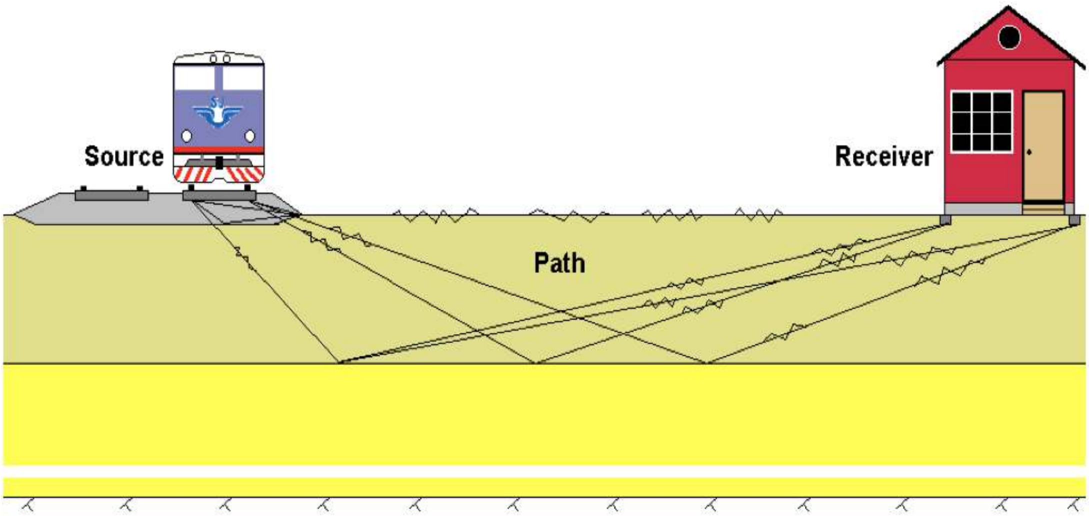

Fig 2.3: Train-Induced Ground Vibration and Its Prediction (Mehdi, 2004)

II.5.1. Blast induced vibrations

The level of ground and structure vibration caused by construction work depends on the construction methods, soil and rock medium, heterogeneity of soil and rock deposit at the site, distance from the source, and characteristics of wave propagation at a site, dynamic characteristics of soil and rocks, response characteristics of fractures and susceptibility rating of the structures. Many of these parameters especially geological and geotechnical conditions of rocks cannot be altered, but the quantity of explosive detonated per delay can be estimated with empirical formula and proposed for blast design(Nateghi, 2012).

Different types of seismic waves are generated due to the explosive blasting process. The first type of waves travels through the media and are known as body waves. Body waves include the compressional P-wave, where the particle motion is longitudinal, and the transverse S-wave, where the particle motion is perpendicular to the direction of propagation. The second type of waves is surface waves, such as the Love wave (Q-wave) and the Rayleigh wave (R-wave) and appears in the presence of a free surface. Surface waves generally travel along the surface at slower velocities than body waves. The R-wave, for homogeneous media, develops due to shear wave reflection on the free surface and has elliptic and retrograde particle motion in a small area near the surface horizontal to the direction of the wave propagation. The amplitude of these surface waves decreases rapidly with depth. While R-waves are generated whenever a free surface exists, Q-waves are observed only when a soft superficial layer covers a stiffer medium. These Q-waves result from the interference caused by multiple S-waves trapped in the soft layer and have transverse particle motion.(Ainalis et al., 2017)

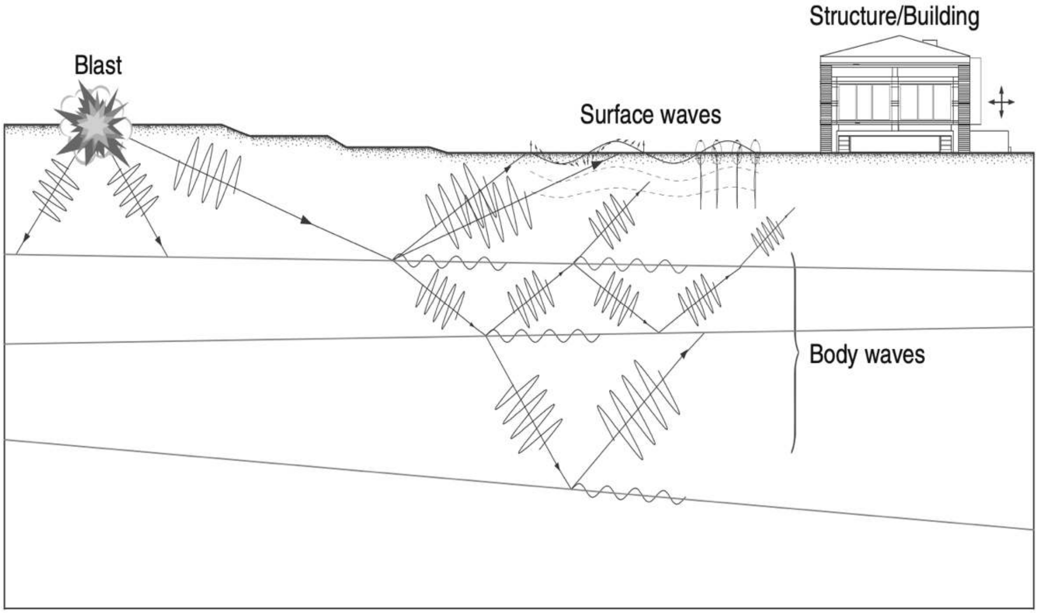

Fig 2.4:Modelling the Source of Blasting for the Numerical Simulation of Blast-Induced Ground Vibrations (Daniel A. et al., 2016)

II.8. Effects of ground vibration

Vibrations may be unacceptable to occupants of buildings because of:

- Annoying physical sensations produced in the human body.
- Interference with activities such as sleep and conversation.
- rattling of windowpanes and loose objects
- Fear of damage to the building and its contents.

II.8. Ground vibration isolation

Ground vibration isolation is a process of isolating a target area, structure or machine from waves propagating comingfrom a vibration source. Waves can be mitigated in three ways:

- Mitigation from the source – avoiding or controlling excessive vibrations.
- Mitigation in the propagating path- use of barriers and trenches to screen waves or modify the attenuation characteristics of the soil.

- Mitigation in the target area or structure – use of base isolations

However, the use of trenches and barriers is the most common method of isolation due their simplicity and low cost compared to other isolation methods. Trenches or barrier can be inserted in the wave propagating path in two ways:

Active isolationinvolves installing the barrier or trench close to the vibration source.

Passive isolationinvolves installing the barrier or trench a far distance from the vibration source.

II.9. Techniques of ground vibration isolation

II.9.1. Open trench

The earliest experimental studies on the effectiveness of trenches(open and in-filled) were carried out by Barkan (1962). In his study, he showed that their effectiveness increases with increasing the depth and the distance for raising frequencies.

(Woods, 1968)conducted an experimental study on active and passive vibration isolation. He also demonstrated that the passive isolation is better than the active for screening the P - body and S-body waves while the active isolation is more suitable for the screening of the Rayleigh waves; moreover, he highlighted that the most relevant geometric parameter in the screening process is the ratio between barrier depth and Rayleigh wavelength. According to several experimental studies, best screening performance occurs when the depth of the trench is equal to the Rayleigh wavelength while the width of the trench is small.

(Beskos et al.,1986) used Boundary Element Method (BEM) to study the effectiveness of open and infilled trenches in vibration screening. However, the soil was assumed to be homogeneous linear elastic.

(Beskos et al., 1990)also proposed a 2D BEM to evaluate the effectiveness of open and infilled trenches and the effect of inhomogeneity of the soil was considered.

(Esmaeili et al., 2014) used a FEM - ABAQUS to model a V-shaped trench, its performance in decreasing train-induced vibration was evaluated in comparing it to a rectangular-shaped trench. It was concluded that the V-shaped trench was more efficient than the rectangular shaped trench.

A field study was carried out by(Toygar and Ulgen, 2021) to investigate the effectiveness of open trench in ground vibration isolation. A highly sensitive was used to measure the amplitudes of vibrations in different test to examine the influence of parameters. It was concluded that the frequency had more influence than the depth in screening effectiveness. Also, it was concluded that better isolation is achieved close to the trench while the effectiveness reduces at farther distances.

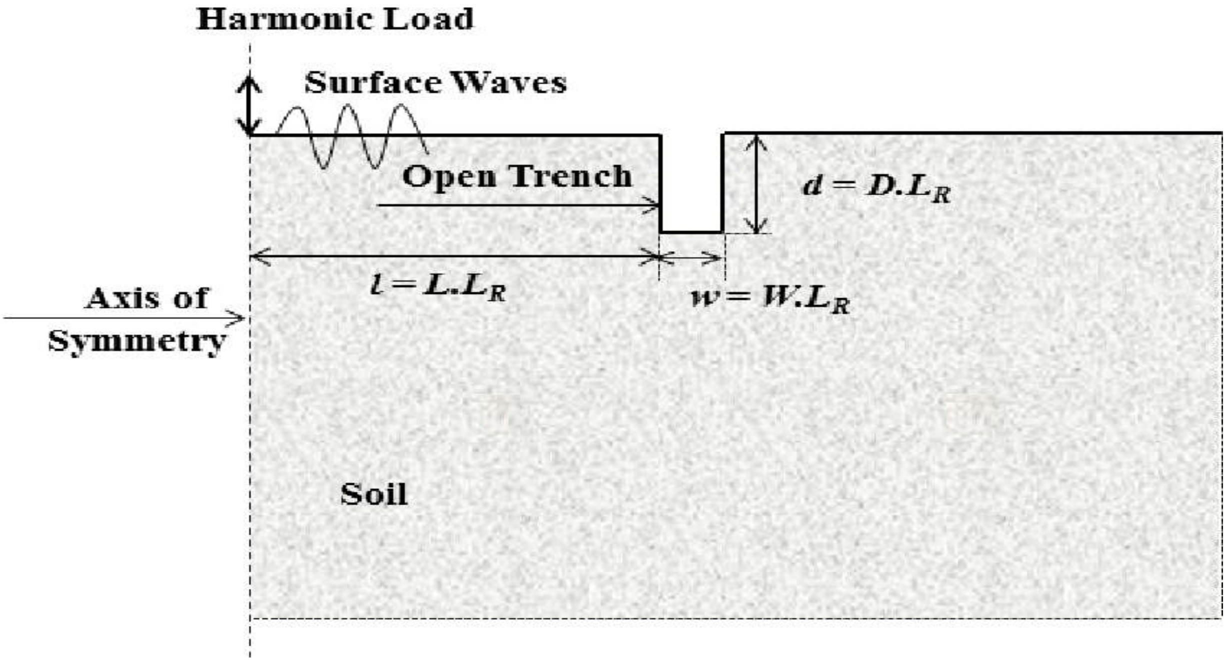

Fig 2.5: Efficiency of Open and Infill Trenches in Mitigating Ground-Borne Vibrations (T Bose, 2018)

II.9.2. Infilled trenches

As a result of difficulties in maintaining open trenches caused by soil instability and water table height inside the trench, infilled trenches have been more practical.Theuseofin-filled trenches has becomeessential in practice when ground vibration waves travel through the trench, where the two mediawithdifferentimpedance characteristicsmeet.Oncevibrationwavesmeetthisinterfacewithimpedance differences, it will undergo mechanisms such as reflection, refraction,scattering, and diffraction of wave energy. Infilled trenches are trenches filled with materials such as concrete, water, geofoam etc. The commonly used in-filling material in previous studies is expanded polystyrene (EPS) geofoam because of its little density.

(Al-Hussaini et al., 1996)used a boundary element method (BEM) algorithm for dynamic analysis of 3D solids to study the effects of various geometric and material parameters on the efficiency of in-filled trenches. Comparisons were made between the concrete barrier and soil-bentonite barrier.

(Murillo et al., 2009) conducted an experimental study using centrifuged small-scale models to determine the efficiency of ground isolation using geofoam barrier. It was concluded that the isolation system depends on the barrier depth.

(Bo et al., 2014) conducted a parametric study to investigate the efficiency of each parameter. It was stated that increasing the depth of the trench, decrease the vertical velocity amplitude reduction ratio while it seems to have no effect on the horizontal velocity amplitude reduction ratio. However, it is only valid for width of 0.1m and depth of 2m. Different phenomenon can be observed for a larger width.

(Zoccali et al., 2015)evaluated the mitigation capacity of infilled trenches in screening train induced vibration. It was stated that the trench dimension is important for effective isolation, but better performance of trench is influenced by the infilled material.

(Ekanayake et al., 2014)made a comparative study of different infill materials in attenuating ground vibrations. EPS geofoam was found to be most efficient fill material, with attenuation efficiency close to that of open trenches. It was concluded that increase in depth of the trench improves the efficiency of EPS geofoam and water as fill materials.

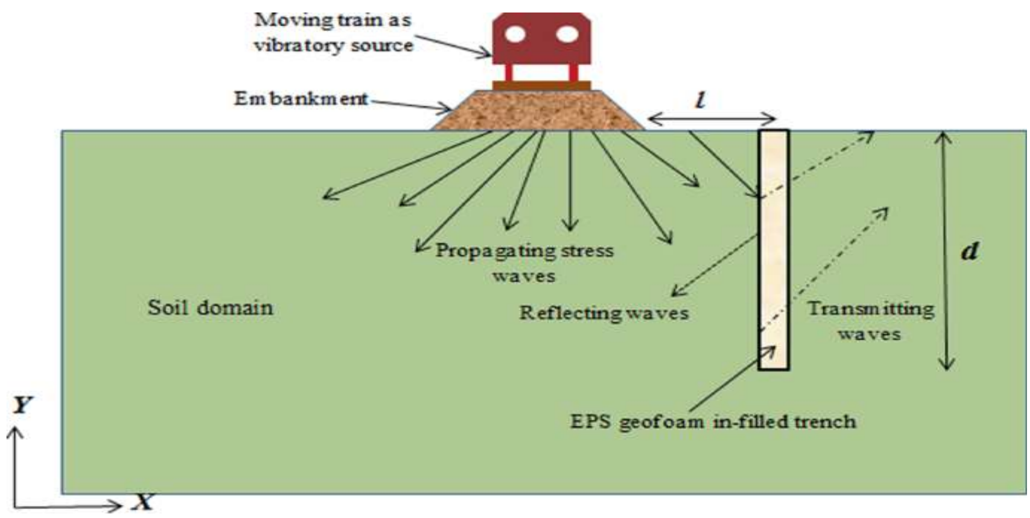

Fig 2.6: ANN-Based Model to Predict the Screening Efficiency of EPS Geofoam Filled Trench in Reducing High-Speed Train-Induced Vibration(Mainak.M et al. 2021)

II.9.3. Multiple Trenches

(Baziar et al., 2019)conducted a study to investigate the screening of ground vibrations induced by high-speed railways using centrifuge modeling. It was concluded that dual geofoam trenches can improve the performance significantly. Results showed that dual geofoam trenches mitigated by ground vibration by 66.1%-78.8% which was initially 44% - 54.5% for a single geofoam trench.

A numerical study was conducted by (Saikia, 2014)using PLAXIS 2D to evaluate the effectiveness of dual geofoam in-filled trench. He. concluded that a dual in-filled trench barrier requires much lesser depth in compared to a single trench to achieve a targeted degree of isolation.

Another studywas conducted by (Pu, 2018)to evaluate the efficiencyof multiple in-filled trenches in ground vibrations screening. It was concluded that the screening efficiency of multiple rows of geofoam-filled trenches increases with increase of number of rows. A depth up to the wavelength is required for high screening performance.

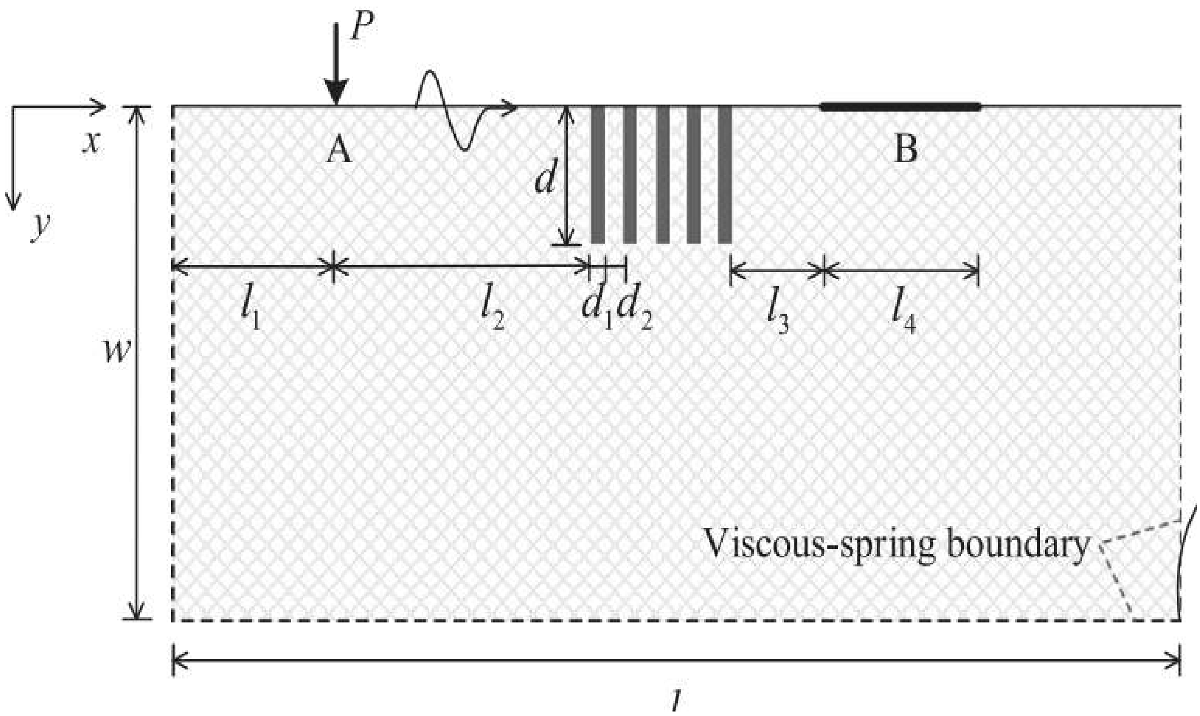

Fig2.6:Multiple trenches (pu, 2018)

II.9.4. Non-Rectangular Trenches

Rectangular trenches are the most common due to its installation rapidity. Only few studies have been done on non-rectangular trenches. However, it is important to know the most effective by comparing the non-rectangular to the rectangular trenches.

(Esmaeili et al., 2014)modeled a V-shaped trench using ABAQUS to evaluate its efficiency in screening train induced ground vibrations. it was concluded that V-shaped trench was more efficient compared to rectangular trench. V-shaped reduced the amplitude reduction ratio before and after by 29% and 36.62% respectively.

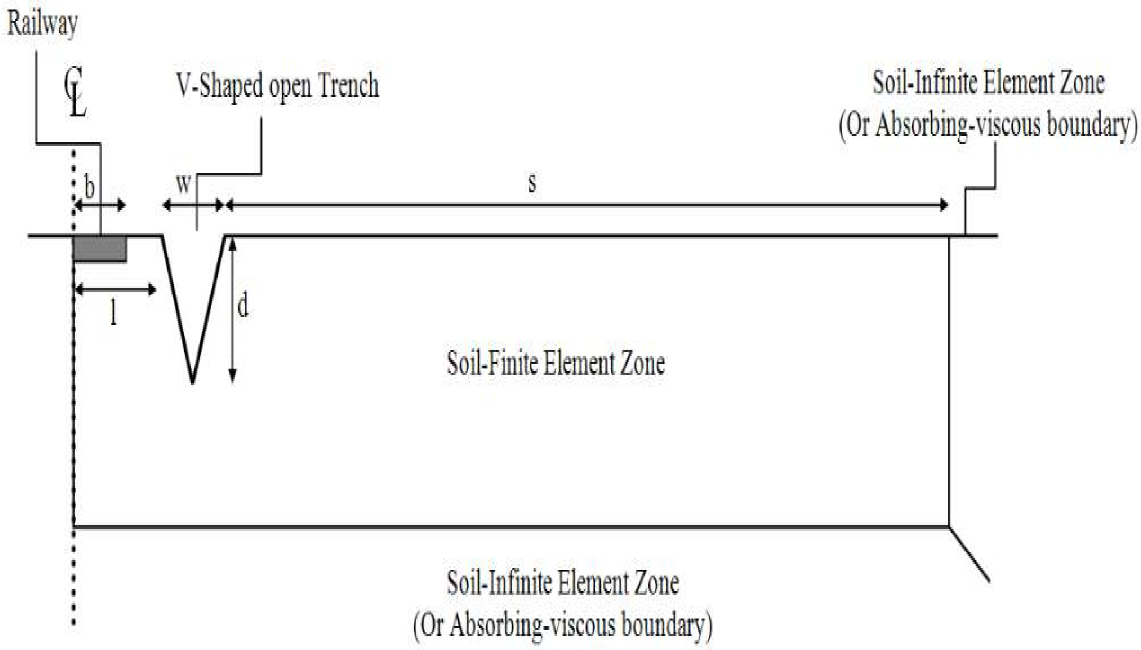

Fig2.7: V-shaped trench (Esmaeili et al., 2014)

II.10. Artificial Neural Networks

An Artificial Neural Network (ANN) is a data processing model based on the way biological nervous systems, such as the brain, process data. They're focused on the neuronal structure ofthe mammalian cerebral cortex, but at a much smaller scale(Dastres and Soori, 2021).Artificial neural networks are a structure formed by connecting artificial nerve cells, similar to the structure of biological nerve cells. Artificial neural networks are formed in layers or layers by the combination of neurons. The neurons used in this structure are in contact with each other to receive inputs and transmit outputs.

In general, the artificial neural network consists of the input layer that transmits the inputs to the next layer, the hidden layer that transmits the information from the input layer to the output layer bypassing certain processes, and the output layer that produces output to the information coming in the input layer(İsmail Akgül, 2022).

II.10.1. Transfer functions

There are different transfer functions can be used as activation function. The three most common functions are threshold, linear and sigmoid.

II.10.1.1. Hard-Limit transfer function:

The hard-limit transfer function limits the output of the neuron to either 0, if the net input argument n is less than 0; or 1, if$n$ is greater than or equal to 0 (Howard Demuth and Mark Beale).

$$\mathbf{a = hardlim\ (wTp - b)}$$

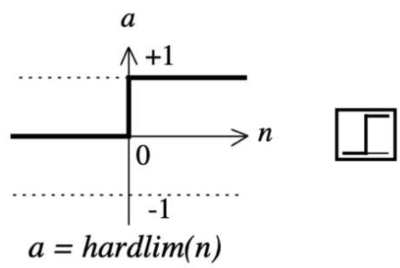

Fig 2.8: hardlim transfer function

II.10.1.2. Linear transfer function:

The linear transfer function calculates the neuron's output by simply returning the value passed to it.

$$a = purelin(n) = purelin(\mathrm{Wp}+ b) = \mathrm{Wp}+ b$$

This neuron can be trained to learn an affine function of its inputs, or to find a linear approximation to a nonlinear function.

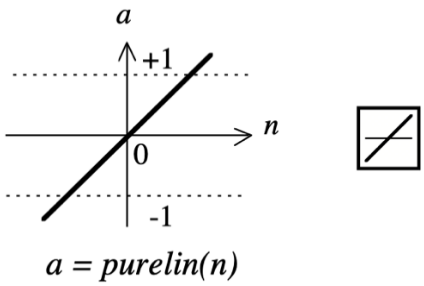

Fig 2.9: purelin transfer function

II.10.1.3.Sigmoid transfer function:

The sigmoid transfer function shown below takes the input, which may have any value between plus and minus infinity and squashes the output into the range 0 to 1. This transfer function is commonly used in backpropagation networks, in part because it is differentiable.

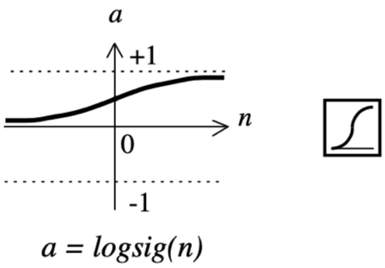

Fig 2.10: logsig transfer function

II.10.2. Neural Network Architecture

A neural network is a set of neurons in a network, so that the signals going out of the neurons become signals going into other neurons. The general architecture of neural networks consists in the representation of neurons in successive layers, the first representing the input layer, the last being the output layer, the intermediate layers being the hidden layers of the network. These layers are called hidden because from outside the network, we cannot clearly analyze their functioning. We only really know the input and output signals of the network. The neurons of the input layer are not really computing neurons, but their only purpose is to normalize the input signals and the distribution of the input signals. In this normalized architecture, the layers of neurons are fully interconnected, i.e., the neurons in one layer are all connected to all neurons in the adjacent layers. This normalized architecture may seem rigid, but it allows a correct representation of most neural networks, while allowing the use of more general training algorithms.

Generally, a neural network behaves, from an external point of view, like a function S that processes data (inputs) and produces a corresponding response (output). The input data can be of any type that can be represented in a binary or numerical way. This data can also be seen as vectors, and the neural network as a vector application**.**(Derbal et al., 2020)

II.10.3. Neural Network Learning

II.10.3.1. Supervised learning

Every input pattern that is used to train the network is associated with an output pattern which is the target or the desired pattern. A teacher is assumed to be present during the training process, when a comparison is made between the network's computed output and the correct expected output, to determine the error.The error can then be used adjust weights of the neurons which results in an improvement in performance of the neural network.

II.10.3.2. Unsupervised learning

In this learning method the target output is not presented to the network.It is as if there is no teacher to present the desired patterns and hence the system learns of its own by discovering and adapting to structural features in the input patterns.The goal of unsupervised learning is to find the structure and patterns from the input data. Unsupervised learning does not need any supervision. Instead, it finds patterns from the data by its own.

II.10.3.3. Hebbian learning

This rule was proposed by Hebb and is based on correlative weight adjustment.This is the oldest learning mechanism inspired by biology.In this, the input-output pattern pairs (xi, yi) are associated by the weight matrix W, known as the correlation matrix.

It is computed as W = $\sum xiyinTi$=1 ----------- (1)

Here yiT is the transposeof the associated output vector yi. Numerous variants of the rule have been proposed.

II.10.3.4. Gradient descent learning

This is based on the minimization of error E defined in terms of weights and activation function of the network.Also, it is required that the activation function employed by the network is differentiable, as the weight update is dependent on the gradient of the error E. Thus if Δwij is the weight update of the link connecting the it□ and jt□ neuron of the two neighbouring layers, then Δwij is defined as, Δwij = η $\partial E \partial wij$----------- (2)

Where, η is the learning rate parameter and $\partial E \partial wij$ is the error gradient with reference to the weight wij

II.10.3.5. Competitive learning

In this method, those neurons which respond strongly to input parameter have their weights updated. When an input pattern is presented, all neurons in the layer compete and the winning neurons undergoes weight adjustment.Hence, it is a winner-takes-all strategy.

II.10.3.6. Stochastic learning

In this method, weights are adjusted in a probabilistic fashion.An example is evident in simulated annealing the learning mechanism employed by Boltzmann and Cauchy machines, which are a kind of NN systems.

Neural Network learning algorithm chart is shown in Fig 2.11

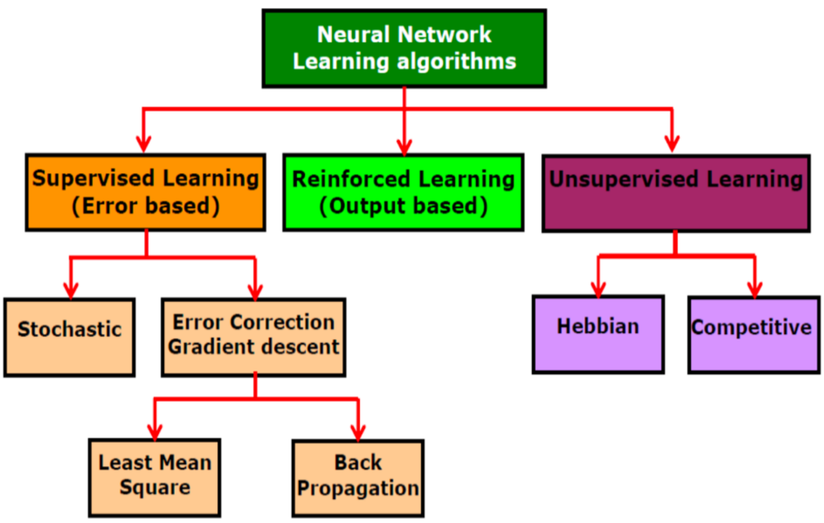

Fig 2.11: Neural network learning algorithm chart

II.10.4. Types of Neural Networks

II.10.4.1. Perceptron

Perceptron model, proposed by Minsky-Papert is one of the simplest and oldest models of Neuron. It is the smallest unit of neural network that does certain computations to detect features or business intelligence in the input data. It accepts weighted inputs and apply the activation function to obtain the output as the final result. Perceptron is also known as TLU (threshold logic unit.Perceptron is a supervised learning algorithm that classifies the data into two categories, thus it is a binary classifier.

II.10.4.2. Feed forward Neural Networks

The simplest form of neural networks where input data travels in one direction only, passing through artificial neural nodes and exiting through output nodes. Where hidden layers may or may not be present, input and output layers are present there. Based on this, they can be further classified as a single-layered or multi-layered feed-forward neural network.Number of layers depends on the complexity of the function. It has unidirectional forward propagation but no backward propagation. Weights are static here. An activation function is fed by inputs which are multiplied by weights. To do so, classifying activation function or step activation function is used. For example: The neuron is activated if it is above threshold (usually 0) and the neuron produces 1 as an output. The neuron is not activated if it is below threshold (usually 0) which is considered as -1. They are fairly simple to maintain and are equipped with to deal with data which contains a lot of noise.

II.10.4.2. Multilayer perceptron

An entry point towards complex neural nets where input data travels through various layers of artificial neurons. Every single node is connected to all neurons in the next layer which makes it a fully connected neural network. Input and output layers are present having multiple hidden Layers i.e. at least three or more layers in total. It has a bi-directional propagation i.e. forward propagation and backward propagation.Inputs are multiplied with weights and fed to the activation function and in backpropagation, they are modified to reduce the loss. In simple words, weights are machine learnt values from Neural Networks. They self-adjust depending on the difference between predicted outputs vs training inputs.

Nonlinear activation functions are used followed by softmax as an output layer activation function.

II.10.4.3. Convolutional Neural Networks

The network contains a three-dimensional arrangement of neurons instead of the standard two-dimensional array. The first layer is called a convolutional layer. Each neuron in the convolutional layer only processes the information from a small part of the visual field. Input features are taken in batch-wise like a filter. The network understands the images in parts and can compute these operations multiple times to complete the full image processing. Processing involves conversion of the image from RGB or HSI scale to grey scale. Furthering the changes in the pixel value will help to detect the edges and images can be classified into different categories.

II.10.4.4. Radial Basis Function Network

Radial Basis Function Network consists of an input vector followed by a layer of RBF neurons and an output layer with one node per category. Classification is performed by measuring the input's similarity to data points from the training set where each neuron stores a prototype. This will be one of the examples from the training set.When a new input vector [the n-dimensional vector that you are trying to classify] needs to be classified, each neuron calculates the Euclidean distance between the input and its prototype.

II.10.4.5. Recurrent Neural Networks

Designed to save the output of a layer, Recurrent Neural Network is fed back to the input to help in predicting the outcome of the layer. The first layer is typically a feed forward neural network followed by recurrent neural network layer where some information it had in the previous time-step is remembered by a memory function. Forward propagation is implemented in this case. It stores information required for its future use. If the prediction is wrong, the learning rate is employed to make small changes. Hence, making it gradually increase towards making the right prediction during the backpropagation.(Team, 2022)

II.10.4.6. The Back propagation Algorithm

The backpropagation algorithm (Rumelhart and McClelland, 1986) isused inlayered feed forward ANNs.This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer.There may be one or more intermediate hidden layers. The backpropagation algorithm uses supervised learning,which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.Theactivation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x multiplied by their ji respective weights w_{ij}):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \qquad (1)$$

Wecan see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function:

$$O_j(\bar{x}, \bar{w}) = \frac{1}{1+e^{A_j(\bar{x}, \bar{w})}} \qquad (2)$$

The sigmoidal function is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. This allows a smooth transition between the low and high output of the neuron (close to zero or close to one). We can see that the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights. Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights to minimize the error. We can define the error function for the output of each neuron:

$$E_j(\bar{x}, \bar{w}, d) = \left(O_j(\bar{x}, \bar{w}) - d_j\right)^2 \qquad (3)$$

We take the square of the difference between the output and the desired target because it will be always positive, and because it will be greater if the difference is big, and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E\left(\overline{x}, \overline{w}, \overline{d}\right) = \sum_{j}\left(O_j\left(\overline{x}, \overline{w}\right) - d_j\right)^2 \qquad (4)$$

The backpropagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of gradient descendent:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \qquad (5)$$

This formula can be interpreted in the following way: the adjustment of each weight ji (w) will be the negative of a constant eta (0) multiplied by the dependence of the previous weight on the error of the network, which is the derivative of E in respect to w. The size of the adjustment will depend on 0, and on the contribution of the weight to the error of the function. This is, if the weight contributes a lot to the error, the adjustment will be greater than if it contributes to a smaller amount. (5) is used until we find appropriate weights (the error is minimal). If you do not know derivatives, don't worry, you can see them now as functions that we will replace right away with algebraic expressions. If you understand derivatives, derive the expressions yourself and compare your results with the ones presented here. If you are searching for a mathematical proof of the backpropagation algorithm, you are advised to check it in the suggested reading, since this is out of the scope of this material. So, ji we "only" need to find the derivative of E in respect to w. This is the goal of the backpropagation algorithm since we need to achieve this backwards. First, we need to calculate how much the error depends on the output, which isthe derivative of E in respect j to O (from (3)).

$$\frac{\partial E}{\partial O_j} = 2\left(O_j - d_j\right) \qquad (6)$$

And then, how much the output depends on the activation, which in turn depends on the weights (from (1) and (2)):

$$\frac{\partial O_j}{\partial w_{ji}} = \frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}} = O_j(1 - O_j)x_i \qquad (7)$$

Andwe can see that (from (6) and (7)):

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1 - O_j)x_i \qquad (8)$$

And so, the adjustment to each weight will be (from (5) and (8)):

$$\Delta w_{ji} = -2\,\eta\left(O_j - d_j\right)O_j(1 - O_j)x_i \qquad (9)$$

We can use (9) as it is for training an ANN with two layers. Now, for training the network with one more layer we need to make some considerations. If we want to adjust ik the weights (let’s call them v) of a previous layer, we need first to calculate how the error depends not on the weight, but in the input from the previous layer. This is easy, we would i ji just need to change x with w in (7), (8), and (9). But we also need to see how the error of ik the network depends on the adjustment of v. So:

$$\Delta v_{ik} = -\eta\frac{\partial E}{\partial v_{ik}} = -\eta\frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial v_{ik}} \qquad (10)$$

Where:

$$\frac{\partial E}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1 - O_j)w_{ji} \tag{11}$$

And, assuming that their k ik are inputs u into the neuron with v (from (7)):

$$\frac{\partial x_i}{\partial v_{ik}} = x_i(1 - x_i)v_{ik} \tag{12}$$

If we want to add yet another layer, we can do the same, calculating how the error depends on the inputs and weights of the first layer. We should just be careful with the indexes, since each layer can have a different number of neurons, and we should not confuse them. For practical reasons, ANNs implementing the backpropagation algorithm do not have too many layers, since the time for training the networks grows exponentially. Also, there are refinements to the backpropagation algorithm which allow a faster learning(Carlos Gershenson, 2003).

II.11. Application of Artificial Neural Network in vibration isolation

(Alzawi and Hesham El Naggar, 2011)conducted a comprehensive experimental and numerical study to evaluate the effectiveness of in-filled geofoam trench barriers for scattering machine foundation vibrations. Two- and three-dimensional time-domain finite element models were developed and verified using the ABAQUS package to assess the effectiveness of various configurations of in-filled geofoam wave barriers. In their numerical study, Multiple Linear Regression (MLR) analysis was utilized to develop a design model, while an artificial neural network (ANN) model was created to predict the protective effectiveness of in-filled geofoam wave barriers in various soil profiles with different geometric dimensions.For the ANN model, a feed forward back propagation network was to predict the average amplitude reduction ratio. Levenberg-Marquardt *trainlm* was the back-propagation training function, *learngdm*was the back-propagation weight/bias learning function, *logsig*was the transfer function for hidden layers while a pure linear transfer function for the output layer and mean squared error function *mse* was the performance function.

(Jayawardana et al., 2019) conducted a numerical study to evaluate the efficiency of geofoam filled trench in ground vibration screening. A database is developed from an extensive study on the effects of the controlling parameters through numerical simulations with a validated finite element (FE) model. Input parameters for the ANN model were excitation frequency, amplitude of load, trench dimensions, soil shear wave velocity, soil density and damping ratio. Amplitude reduction ratio was considered as output. A multilayer feed forward network was used and trained with the Levenberg-Marquardt algorithm. Neural networks with different configurations were evaluated by comparing coefficient of determination (R^2) and mean square error (MSE).

II.12. Conclusion

This chapter has described the relevant literature and discussed ground vibration propagation and methods used by previous researchers to mitigate ground vibrations. Based on the review, many studies were conducted on the use of open trenches as wave barriers for vibration isolation. It was demonstrated that open trenches are the most effective wave barriers for vibration screening. However,there was no comprehensive method for determining trench configuration for open trenches.

CHAPTERIII NUMERICAL MODELLING AND DATABASE DEVELOPMENT

III.1. Introduction

This chapter includes 3D modelling of the vibration medium (soil), a vibration source, a trench and acceleration measure points using a FEM software (COMSOL Multiphysics). Firstly, a trench was inserted in the propagating path of the wave to evaluate the acceleration. Acceleration evaluation was later made in the absence of a trench. For both cases (with trench and without trench), Acceleration was evaluated at 25m away from the vibration source. The trench is placed at 15m away from the vibration source and 10m from the measure point. Nine different soils with distinct Young's Modulus, Poisson'sratio and densities were studied and evaluated. Results from these studies were obtained and database were generated for the Neural Network.

III.2. COMSOL

COMSOL Multiphysics software offers several simulation modules. This software is a finite element tool for solving partial differential equations (PDEs), its distinctive feature being a database of equations for modeling physical phenomena, such as material deformation, fluid flow and electrostatics.

COMSOL Multiphysics is a powerful interactive environment for modeling and solvingall kinds of scientific and technical problems. The software provides a powerful integrated environment with a Model Builder that enables complete model overview and access to all functionalities. Using COMSOL Multiphysics, we can easily extend classic models for a single type of physics to Multiphysics models that solve coupled physical phenomena simultaneously. Plus, it does not require an in-depth knowledge of mathematics or numerical analysis.

By using the integrated physical user interfaces and advanced support for material properties, it is possible to build models by defining the physical quantities involved,such as material properties, loads, stresses, sources, and flows, rather than by defining the underlying equations. We can always apply these variables, expressions, or numbers directly to solid and fluid domains, boundaries, edges, and points, regardless of the calculation mesh. COMSOL Multiphysics then compilesa set of equations representing the entire model.

We can access the power of COMSOL Multiphysics as a stand-alone product via a flexible graphical user interface (GUI), or by programming a Java script orMATLAB (requires COMSOL’sLive Link for MATLAB). Using these physical interfaces, we have different types of studies, including:

- Stationary or temporal (transient) studies.
- Linear and non-linear studies.
- Eigenfrequency, modal and frequency response studies.

III.3. FE MODEL

A 3D FE model was developed using COMSOL Multiphysics.The model is composed of three domains:

Domain 1: represents a homogeneous, finite, and elastic soil as a media for vibration propagation. The geometryis characterized by a length of 200m, width of 100m and 50m deep.

Domain 2: represents a trench for mitigating ground vibrations. The trench is characterized by a depth of 2m, width of 1m and length of 5m.

Domain 3: represents the vibration source of the model. It consists of a 0.1 x 0.1 concrete block where the acceleration was prescribed.

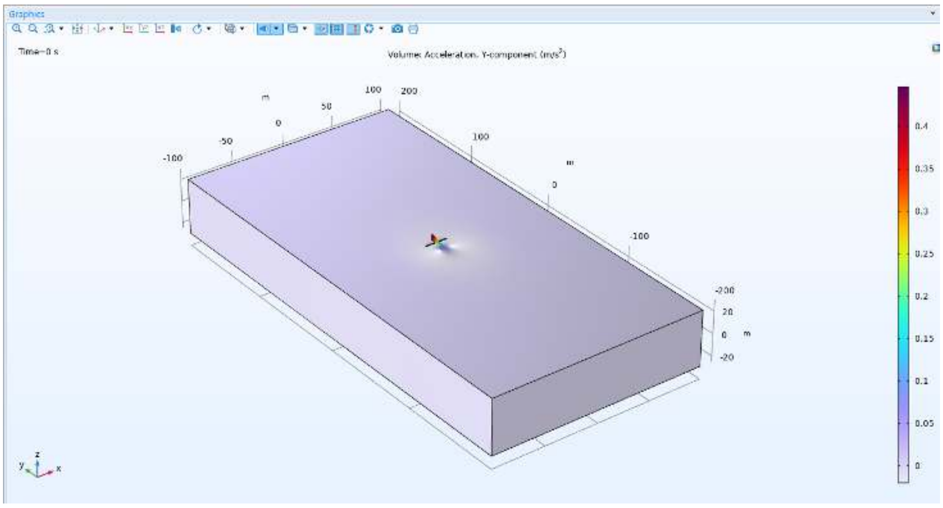

Fig 3.1: FE model

III.3.1. Model Physics and study

The chosen physics interface the FE model was the solid mechanics interface. The model materials were all considered to be linear elastic materials. The boundary conditions were fixed constraints at all sides except the ground surface.A time-dependent study was conducted for the FE model. The study time varies from 0s to 5s with a step of 0.5s and was physics controlled.

III.3.2. Excitation

A harmonic acceleration of 3.6m/s^2in was prescribed along the Y axisat the vibration source (domain 3). Damping was introduced in terms of Rayleigh damping.

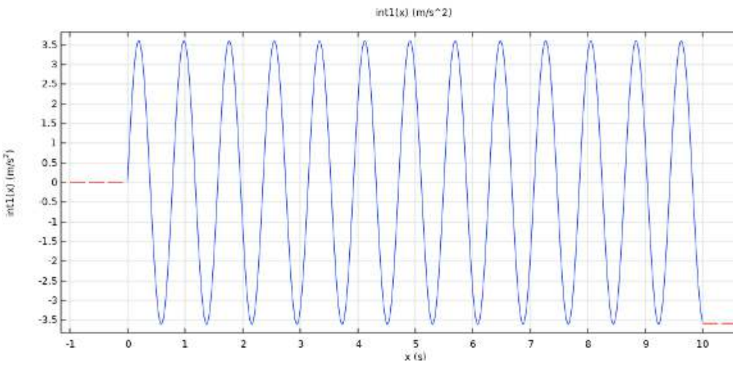

Fig3.2: Prescribed acceleration in the vibration source

III.3.3. Mesh

A normal mesh size was chosen for the geometry to assure the desired accuracy in the solutions during the study. The normal mesh was physics controlled.

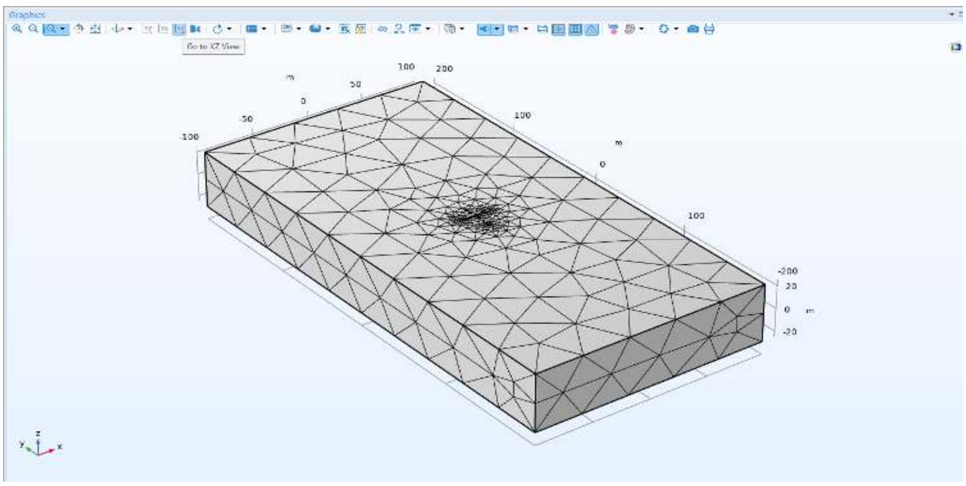

Fig3.3:Meshing for the FE model

III.4. SoilParameters

The following soils as shown in Table 3.1 were used to in FE modeling. All soils were studied first without trench and then with open trench. Only a time-dependent study using these soil parameters subsequently was conducted to yield accelerations in absence of trench. On the other hand, a parametric study on the trench dimensions was done using these soils for case of an open trench.

Table 3.1: soil properties used in modelling

	Young'sModulus(MPa)	Density(kg/m³)	Poisson's ratio
Soil A	100	1900	0.3
Soil B	378	2100	0.3
Soil C	72	1700	0.4
Soil D	150	2000	0.25
Soil E	50	1750	0.4
Soil F	84	1800	0.35
Soil G	173	2000	0.35
Soil H	224	2050	0.25
Soil I	64	1850	0.35

III.5. Modelling without trench

A model was first studied without a trench to evaluate the acceleration at 25m from the vibration source. The model is composed of only two domains i.e. the soil media and the vibration source with the same aforementioned geometrical characteristics.3.6m/s² harmonic acceleration was prescribed along the Y axis of the model.

For accuracy of the study solutions, a normal mesh size was used. The model was studied using a time-dependent study of 0s to 5s with a step of 0.5s. At a measure point of 25m from the source, results of accelerations were generated. 11 accelerations were obtained andeach acceleration represents a 0.5s step.

This study was conducted for 9 soils with distinct soil parameters (density, young's modulus, and Poisson's ratio). This was done by changing the materials of domain 1 (soil media) in the model. The considered soils are shown in Table 1.

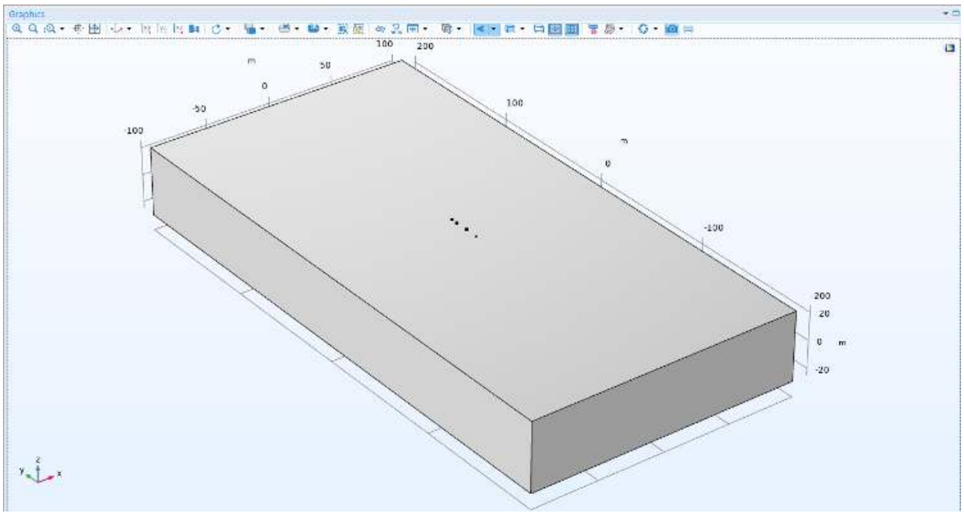

Fig 3.4:modelling without trench

III.6. Modelling with Open trench

A trench was installed in the wave propagation path to evaluate acceleration mitigation. The trench was placed at 10m away from the evaluation point and 15m from the vibration source.This model contains three domains: the soil media, the trench, and the vibration source. The geometries for the three aforementioned domains were used for this model.

The model was excited with a 3.6m/s² harmonic acceleration. A normal mesh size which is physics controlled was used for this study. A time-dependent study was done for 0s to 5s with a step 0.5s.

A parametric sweep was done for the geometric parameters of the trench such as the width, the depth, and the length. This was done for all the nine soils type subsequently.The width was varied from 0.5m to 3m with a step of 0.5s. The depth was varied from 1m to 10m with a step of 0.5m. The length was also varied from 5m to 20m with a step of 2.5m.

Accelerations were generated at the evaluation point (25m from the source). Physics solution from the parametric sweep generated 11 accelerations. Each acceleration represents a 0.5s step time.

This study was conducted for 9 soils with distinct soil parameters (density, young's modulus, and Poisson's ratio).

Table 3.2: parametric sweep for open trench

Trench dimension	Start	Step	Stop
Width (m)	0.5	0.5	3
Depth (m)	1	0.5	10
Length (m)	5	2.5	20

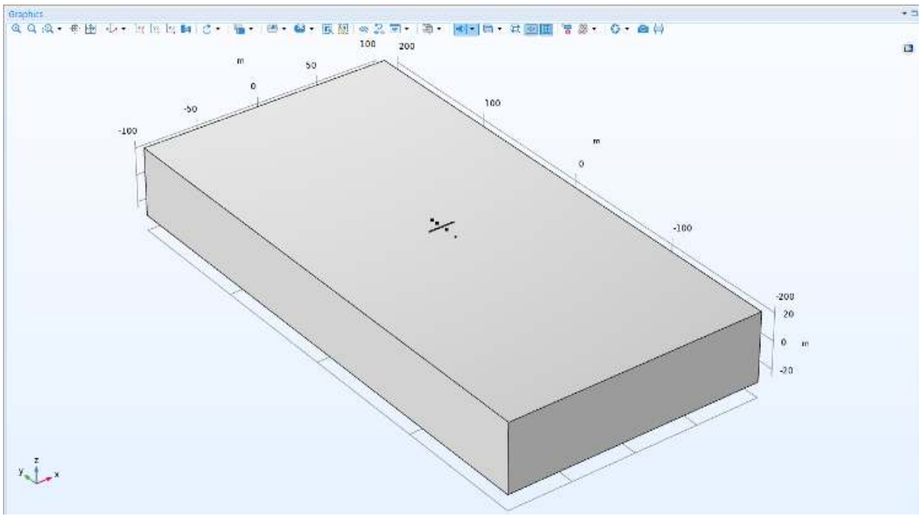

Fig 3.5:modelling with open trench

III.7. Parametricstudy

A parametric study was conducted using results obtained from performing a parametric sweep on FE model for one of the considered soils with young's modulus E=150MPa, density=1800kg/m³ and Poisson's ratio=0,25. In this study, the influence of the different trench dimension was evaluated in reducing the prescribed acceleration on the FE model. This consists of varying a particular trench dimension whilefixing other dimensions. Observations were made and the contribution of each of the trench parameters (width, depth and length) was analyzed.

III.7.1 Influence of trench depth

To examine the influence of the trench depth, the depth was varied from 1m to 10m with a step of 0.5m while the width and length were fixed at 1.5m and 10m respectively. Fig 3.6 shows peak acceleration with variation in depth.

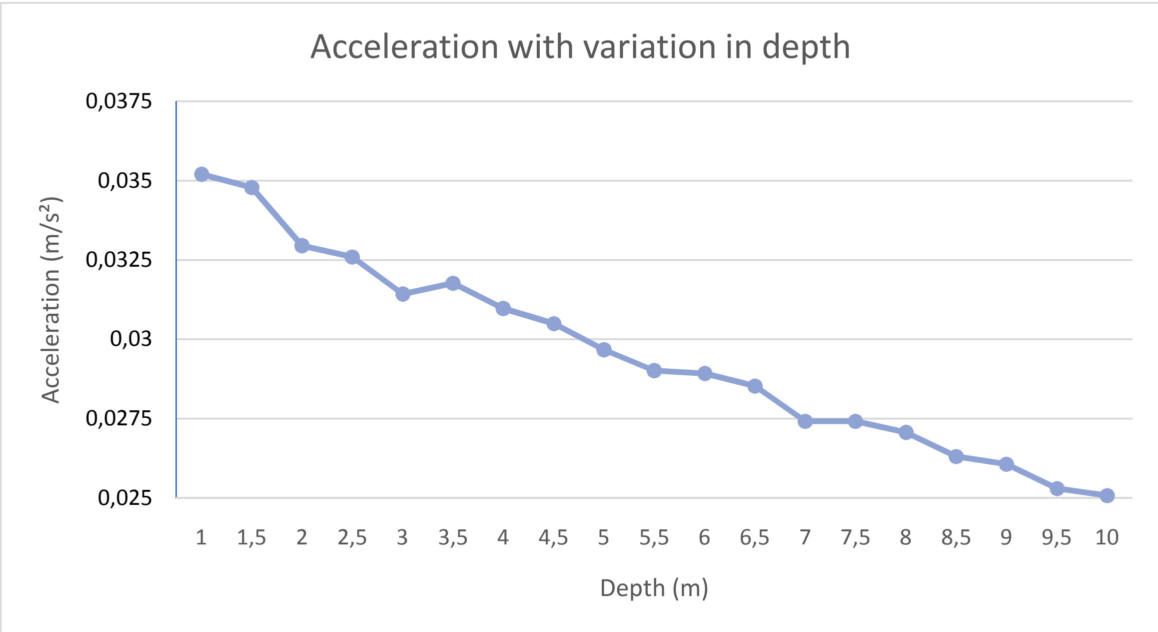

Fig 3.6. Influence of the depth

III.7.2 Influence of trench width

To evaluate the influence of the width in acceleration reduction. It was varied from 0.5m to 3m with a step of 0.5m while the depth was fixed at 5m and the trench length was fixed at 10m. The change in acceleration with variation in width is shown in Fig 3.6.

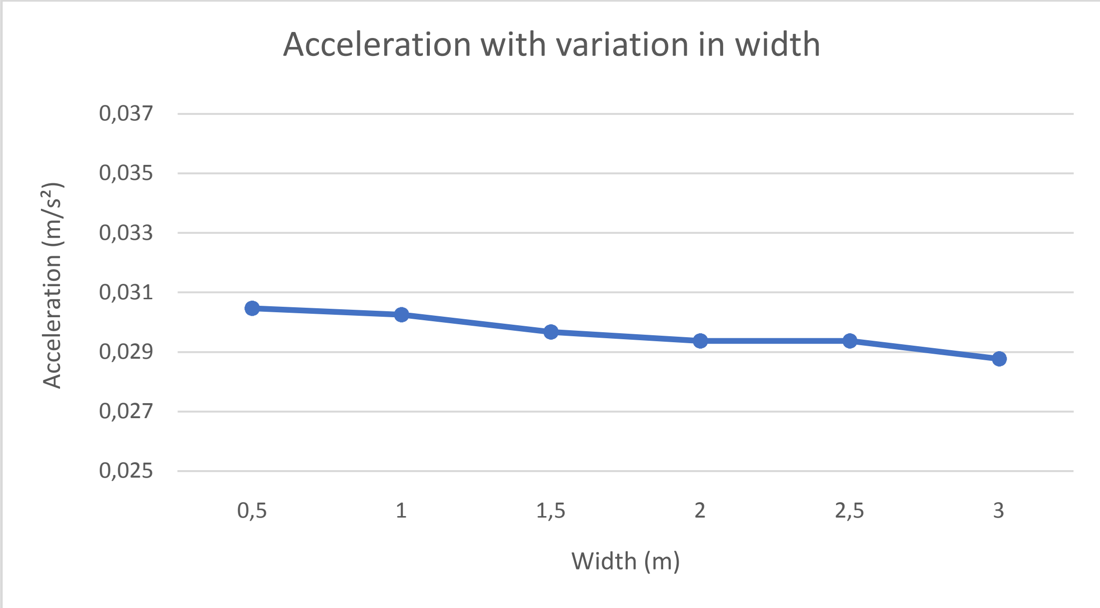

Fig 3.7 Influence of the width

III.7.3 Influence of the length

To analyze the contribution of the length in acceleration reduction, there was variation of the length from 5m to 20m with stepping of 2.5m. In this process, the width and depthwere fixed at 1.5m and 5m respectively. Fig 3.7 shows peak accelerations with variations in length.

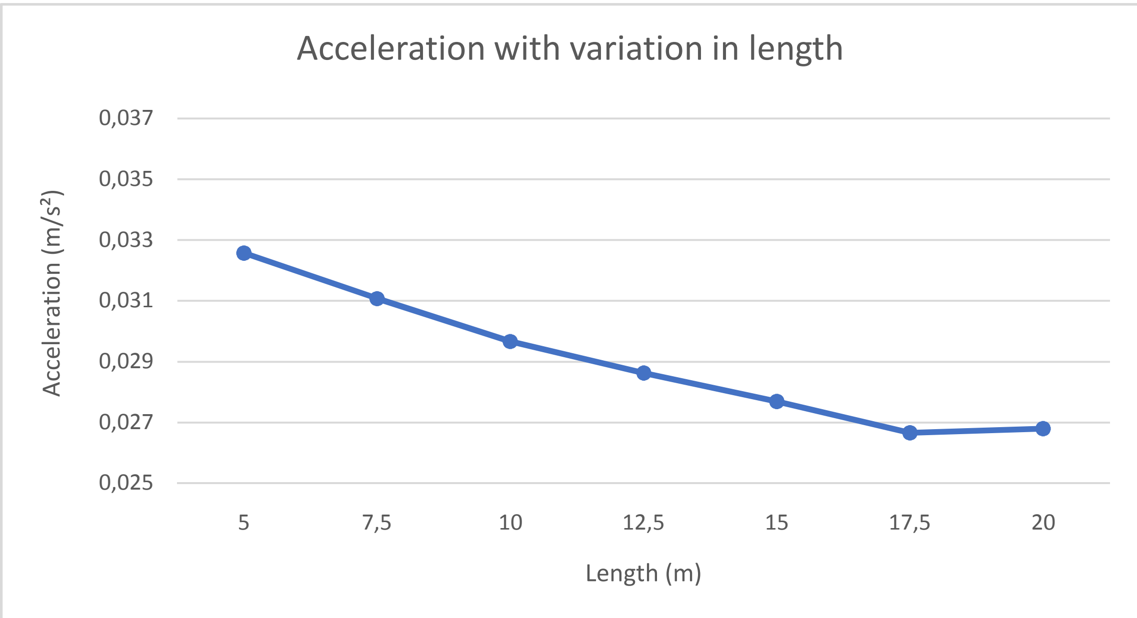

Fig 3.7 Influence of the length

III.8. Database development

Results generatedfrom point evaluation in the COMSOL model builder made a database which will be used for Artificial neural network. The database was created by exporting the generated results from COMSOL. This was done for two models: model without trench and model with open trench. The compositions of these databases consist of the parametric sweep results from the FE model with open trench and a time-dependent acceleration results for the FE model without trench.

III.8.1. Database for model without trench

Ninedatasets were developed from the model without trench.This model isn't composed of trench so there wasn't variation of trench dimensions. The databases contain time-dependent accelerations evaluated at 25m from the vibration source. For every datasets, there are eleven accelerations such that there is an acceleration value atevery 0.5s starting from 0s to 5s.

III.8.2. Database for open trench model

This model was used to develop nine datasets with each database representing a specific soil with parameters as shown in table 3.1. These databases are composedof time-dependent accelerations and trench parameters including trench width, depth as well as trench depth.The values for the parameters are as follows:

- Width which varies from 0.5m to 3 with 0.5m stepping
- Depth which varies from 1m to 10m with 0.5m stepping
- Length which varies from 5m to 20m with 2.5m stepping

Each datasets contains 8778 rows of data was generated in a way such that varying the three trench parameters and combining them randomly and simultaneously yielded a value for acceleration. The soil parameters were not included in the database since they were already defined in the model during the parametric sweep.

III.9 Conclusion

In this chapter, an FE model was developed, database for ANN was generated and a comprehensive parametric study was conducted. It can be concluded that installing an open trench cause some reduction in ground vibration and that depth of the trench is more significant than the width and length in vibration mitigation.Acceleration attenuation for depth, width and length are 28.72%, 5.60% and 17.75% respectively.

CHAPTER IV ARTIFICIAL NEURAL NETWORK

IV.1. ANN structure

Artificial Neural Networks (ANN) are composed of an input layer, an output and one or multiple hidden layers. These layers contain processing elements (neurons) which are interconnected by variable weights. Each neuron receive weighted output from the neurons in the previous layer and the node input is produced by adding the result of summation to a bias.

$$(n)_i = \sum_{j=1}^{n} wijX_J + w_b \qquad (13)$$

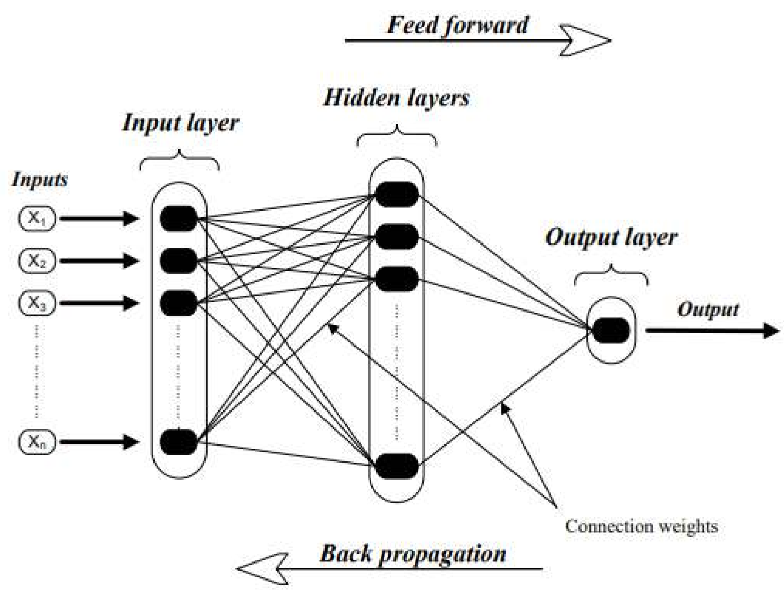

Fig 4.1: Structure of an ANN

IV.2. Problem definition

The objective of the developed ANN is to evaluate the efficiency of an open trench in the mitigation of ground vibration. The end-result is to enable choosing the appropriate trench dimensions for a particular soil to achieve a desired level of isolation.

The FE model was used to generate datasets for nine different soils in the presence and in absence of a trench. Young's modulus, Poisson's ratio, density, trench width, trench depth and length were used as input. Output of the neural network was Amplitude reduction ratio at 10m from trench and 25m from the source.

IV.3. Database

The ANN model ability to evaluate the open trench efficiency will largely depend on how comprehensive the database is. In other words, it will depend on the availability of sufficient data points to teach the ANN model the relationships between the adopted parameters and the averaged amplitude reduction ratio. Furthermore, the data points must cover the entire range over which the different input variables are expected to be. The datasets used in training and testing the ANN model is obtained from the numerical study conducted using COMSOL Multiphysics. Given the fact that ANNs are very sensitive to absolute magnitudes, the variables should be normalized in a way to produce a set of data values within the same order of magnitude. This is because when the variables are different in order of magnitude, fluctuations in the first input parameter will tend to swamp any importance given to the second input parameter, even if the second input is much more important in predicting the desired output. Thus, all data points should be scaled and normalized so that they correspond roughly to the same range of values. Scaling the data will avoid saturation of the hidden nodes and will ensure that all variables have a fair impact on the output. Therefore, the training data should be scaled such that the processed data lies in the range of [-1, 1]. The formula below was used for normalizing all datasets.

$$(X_i)_N = 2 \times \left(\frac{Xi - Xmin}{Xmax - Xmin}\right) - 1 \qquad (14)$$

Xi = i^{th} value of an input parameter

$(Xi)_N$ = Normalized value of an input parameter

Xmin = Minimum value of an input parameter

Xmax = Maximum value of an input parameter

IV.3.1. Training Datasets

For proper training of the ANN, there is a need to enrichen the artificial neural network with lots of data. In this study, six datasets were used for the training and it represent 66.66% of the total database. These datasets were developed from parametric sweep using COMSOL. Before presenting these datasets to the ANN, they were treated and the number of data were reduced. The treatment is in a sense that only trench configuration (combination of width, depth and length) that yielded peak accelerationswere used for the training datasets. This process saw the datasets reduce from 8778 to 798 rows of data for width, depth, length and their corresponding accelerations. This process was done because peak accelerations are more intense plus only peak accelerations were used in determining amplitude reduction ratios.

Input parameters

- Trench parameters

Width of the trench; varies from 0.5m to 3m with 0.5m step and contains 798 elements

Depth of the trench: from 1m to 10m with 0.5m step and contains 798 elements

Length of the trench: from 5m to 20m with 2.5m stepandit contains 798 elements

- Soil parameters

For the soil parameters, there wasn't variation in their value. They were entered as constant values and they all contain 798 elements just like the trench parameters.

Young modulus E: 72MPa, 84MPa, 150MPa, 173MPa, 224MPa, and 378MPa

Poisson's ratio: 0.4, 0.35, 0.25, 0.35, 0.25, 0.3

Density: 1700kg/m^3, 1800kg/m^3, 2000 kg/m^3, 2000 kg/m^3, 2050 kg/m^{3}and2100kg/m^3

The input elements for data training is 6 input parameters × 4778 elements. The 4778 elements include data for an input parameter for the six datasets.

Output parameter

The output for the ANN training is the amplitude reduction ratio (Ar). This is ratio between peak acceleration with trench and peak acceleration without trench. Peak accelerations without trench were generated in COMSOL using the model without a trench. On the other hand, peak accelerations with trench were generated from the treated parametric sweep results. There are six peak accelerations without trench as they correspond to the six soils (young's modulus, density and Poisson's ratio) while treated peak acceleration contains 798 for each dataset.

The value of each peak acceleration without trench was entered and contained the same number of elements (798) as peak acceleration with trench. This process was done for all six datasets and the output contained a total of 1 × 4778 elements.

IV.3.2 Testing Datasets

Three soil datasets were used to test the trained ANN. The testing data represents 33.33% of the total datasets. The same process of treating the generated datasets from COMSOL as discussed for the training data was also done for testing datasets.

<u>Input parameters</u>

- Trench parameters:

Width of the trench; varies from 0.5m to 3m with 0.5m step and contains 798 elements

Depth of the trench: from 1m to 10m with 0.5m step and contains 798 elements

Length of the trench: from 5m to 20m with 2.5m step andit contains 798 elements

- Soil parameters:

For the soil parameters, there wasn't variation in their value. They were entered as constant values and they all contain 798 elements just like the trench parameters.

Young modulus E: 50MPa, 64MPa, 100MPa

Poisson's ratio: 0.4, 0.25, 0.3

Density: 1750kg/m^3, 1850kg/m^3, 1900kg/m^3

The input elements for data training is 6 input parameters × 2394 elements. The 2394 elements include data for an input parameter for the threedatasets

IV.4. Neural Network type

IV.4.1 Feed-Forward Neural Network

Feed-forward neural network model is widely used in engineering applications. In feedforward neural networks, neurons are arranged in layers and all the neurons in each layer are linked to all the neurons in the next layer. In general, the feed-forward neural network consists of an input layer, output layer and one or more hidden layers of neurons. The phrase "feed-forward" indicates that the data moves forward from one layer to the next during ANN modelling. The input layer receives input information and passes it forward to the neurons of the hidden layer, which in turn passes the information to the output layer. The output from the output layer is the corresponding prediction of the model for the data set supplied at the input layer. To construct a stable feed-forward neural network for a particular problem, the optimum number of neural units in each layer is selected using a trial and error approach.

IV.4.2. Back-Propagation Learning Algorithm

Learning algorithms are techniques used to establish connections (i.e. weights and biases) between neurons forming the network structure and to adjust both weights and biases to obtain the desired values. There are two broad categories of algorithms: unsupervised (weights and biases are modified in response to network inputs only) and supervised (weights and biases are modified in order to move the network outputs closer to the targets) (Haykin S., 1999).

In the supervised learning process, the neural network is trained with the help of data that contains a set of inputs and corresponding target values. In unsupervised learning there is no specific response required, but rather the response is based on the networks ability to organize itself. The vast majority of learning in engineering applications involves supervised learning.

One of the well-known supervised training algorithms for the feed-forward neural networks is the back-propagation algorithm. In this algorithm a gradient descent technique is applied to minimize the error for a particular training pattern in which it adjusts the weights by a small amount at a time.

IV.5. ANN model

The input parameters for the model includesyoung’s modulus, Poisson’s ratio, density, trench width, trench depth and length. Amplitude reduction ratio (Ar) was the model’s output.

$$\mathrm{Ar} = \frac{\text{Peak acceleration with trench}}{\text{Peak acceleration without trench}}$$

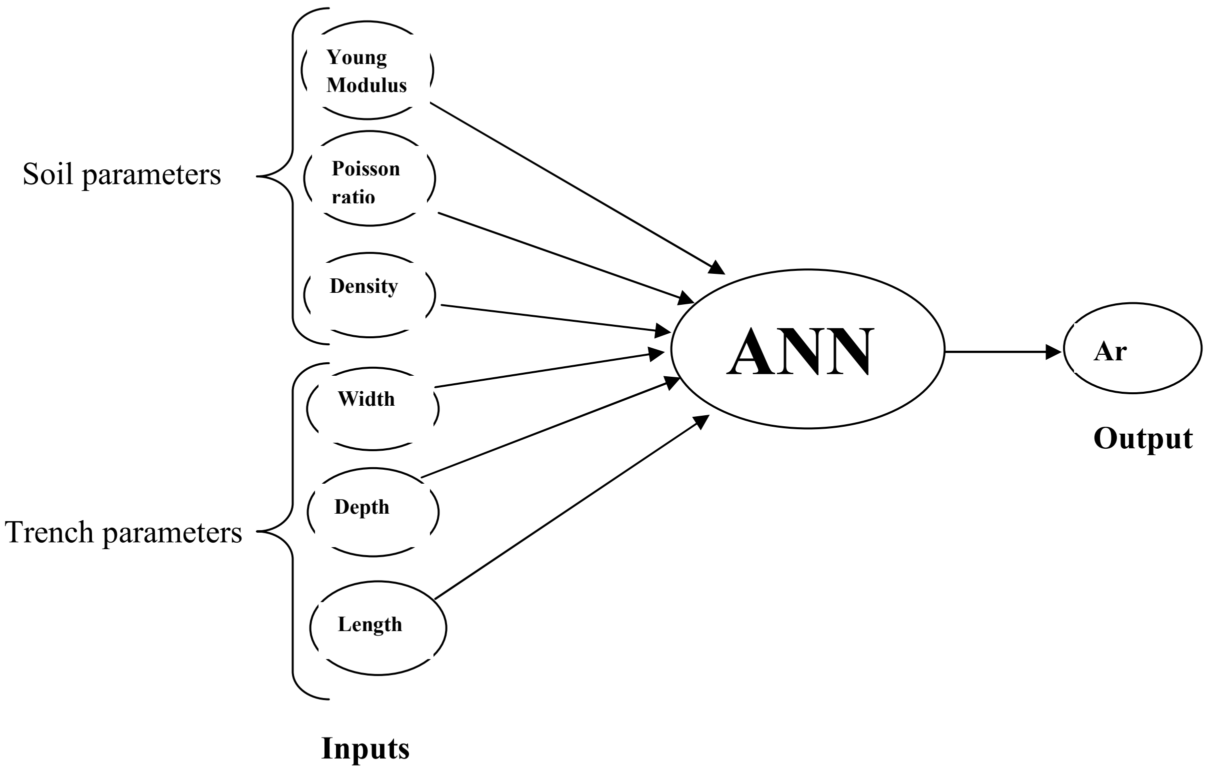

Fig 4.2: ANN model with inputs and output

IV.6. ANN architecture

The neural network was developed using MATLAB (R2015b). A feed forward network used for the programme. Levenberg-Marquardt training Algorithm (*trainlm*) was used for training the network. Transfer functions used were tangent sigmoid and pure linear functions. hyperbolic tangent sigmoid (*tansig*) function is theused non-linear function while pure linear (*purelin*) was the linear function for the output layer. The Mean square error (*MSE*) was used to measure the performance of the ANN model.

The datasets were divided into two subsets: training and testing. The training data is used to train the model to recognize the patterns and relations between input and output data. The final model is tested with the testing data set, which was not used during training, to ensure that predictions are accurate and not influenced by the training stage. Before training, all data (i.e. inputs and targets) were scaled to make them fall in the range [-1,1]. This pre-processing step is called normalizationand increases the efficiency of the Neural network training.

The adopted criteria in this study is that datasets was divided into two subsets. 66.66% of the data was used for trainingand 33.33%was used as a completely independent test of network generalization.

The number of neurons in the hidden layer was determined by training several networks with different numbers of hidden neurons and comparing the predicted results with the desired output. In other words, the number of the hidden neurons was optimized, using trial and error, to minimise the mean squared error as well as to avoid under-fitting (i.e large training and validating errors) and prevent over-fitting. In this study, one layer with different number of neurons was considered for ANN model. The ANN architecture and the structure of the three layers is shown in Fig 4.3 and Table 4.1 respectively.

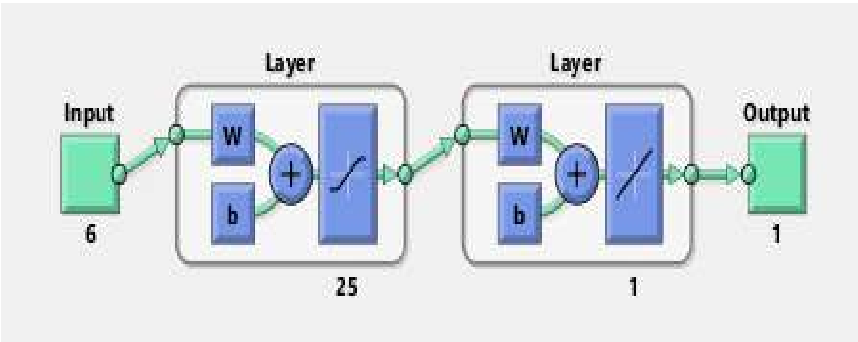

Fig 4.3. Architecture of ANN model

Table 4.1: structure of the three layers

Parameters	ANN
Number of Input layer neurons	6
Number of hidden layers	1
Number of neurons in the hidden layer	25
Transfer function in the hidden layer	tansig
Transfer function in the output layer	purelin
Number of output layer neurons	1

IV.7. Conclusion

This study is focus at demonstrating the use of artificial neural networks to predict the averaged amplitude reduction ratio for using open trenches as a wave barrier to mitigate ground vibrations. A comprehensive database was developedusing COMSOL and was used for training and testing the ANN model. It can be concluded that:

1. The ANN model is a viable method for predicting the amplitude reduction ratio. It effectively captured the interrelationships model variables.
2. The developed ANN model can be used as a design tool to predict the optimum trench dimensions.

CHAPTER V: RESULTS AND DISCUSSION

V.1. Introduction

This chapter presents the results from the ANN model. It is composed of the training result, testing results, performance in terms of mean squared error and prediction results. An in-depth analysis was made on the obtained results and then conclusions were made based on the results.

V.2. ANN Training

The adopted inputs used in training the ANN model for the amplitude reduction ratio prediction are stated in Table 4. The datasets consist of 8778 data points. A successfully trained ANN model should give accurate output predictions, especially for any new testing data that has not been used by the model. Moreso, good ANN models normally have only slight difference between their validating and testing errors. The performance of the ANN model was assessed at the training stage statistically based onmean-square error (MSE) between the ANN model predictions andtraining datasets.

Satisfactory performance of the training process was verified through using the ANN model to predict the averaged amplitude reduction ratio based on the whole training data using six input variables. A regression R-value of 0.99803 was gotten for the total response based on the trained network using the trainingdatasets (66.66% of datasets). The best training performance of 6.5451×10^{-6} of 1×10^{-7} was achieved and the error is acceptable

In the training stage, a linear regression analysis was performed on the network response. The performance of ANN model and the number of epochs were also evaluated. Figures 5.1, 5.2 and 5.3 shows the linear regression results between the network outputs and the corresponding targets for the training phase,the number of epochsand the performance of ANN model using MSE respectively.

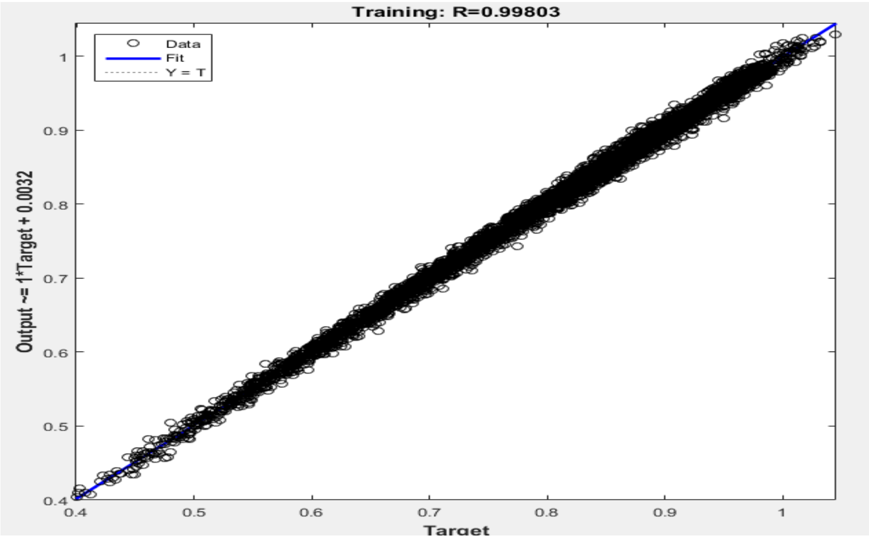

Fig 5.1: Linear Regression for ANN training

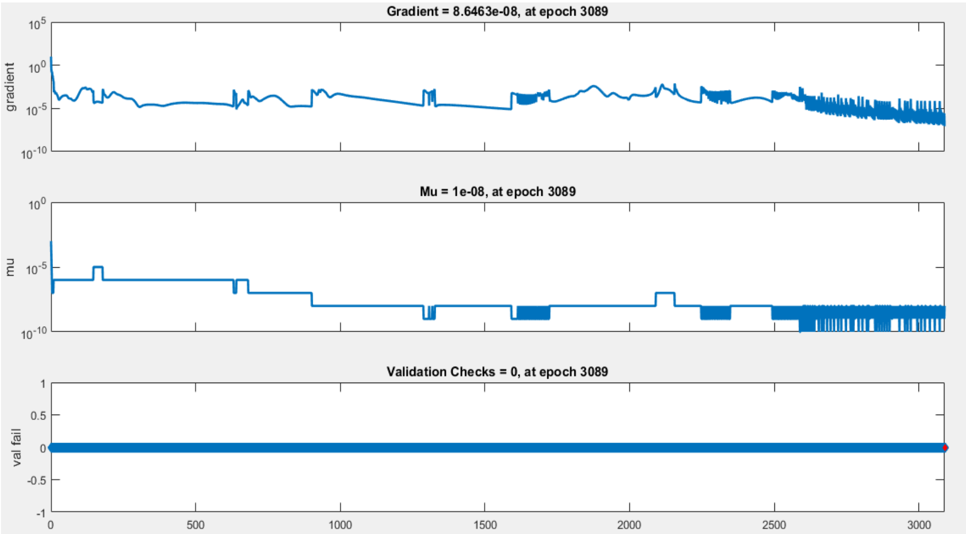

Fig 5.2: Number of epochs

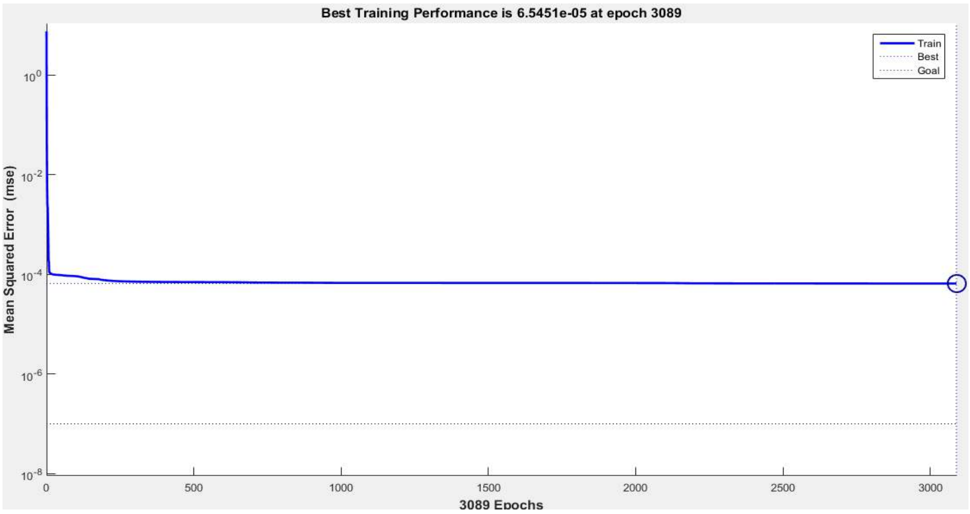

Fig 5.3: Performance of ANN model

V.2. ANN Testing

To confirm the generalization capacity of the ANN model, it was tested using the testing data (33.33% of the totaldatasets). These test data were not initially presented to the ANN model, therefore predictive capacity for new data can be evaluated. The six input parameters of the testing data points were introduced to the ANN model. The test datasetsconsist of 2394 data points.

Just like in the training phase, the model predictions compare well with the actual provided data; the data points were mostly located on and just few slightly away from the equity line. Hence, the ANN issaid to be satisfactorily and can generalize the prediction of the amplitude reduction ratio (Ar) for the considered open trench. A linear regression R of 0.98445 was achieved. The linear regression between targets and predicted output is shown in Fig 5.4.

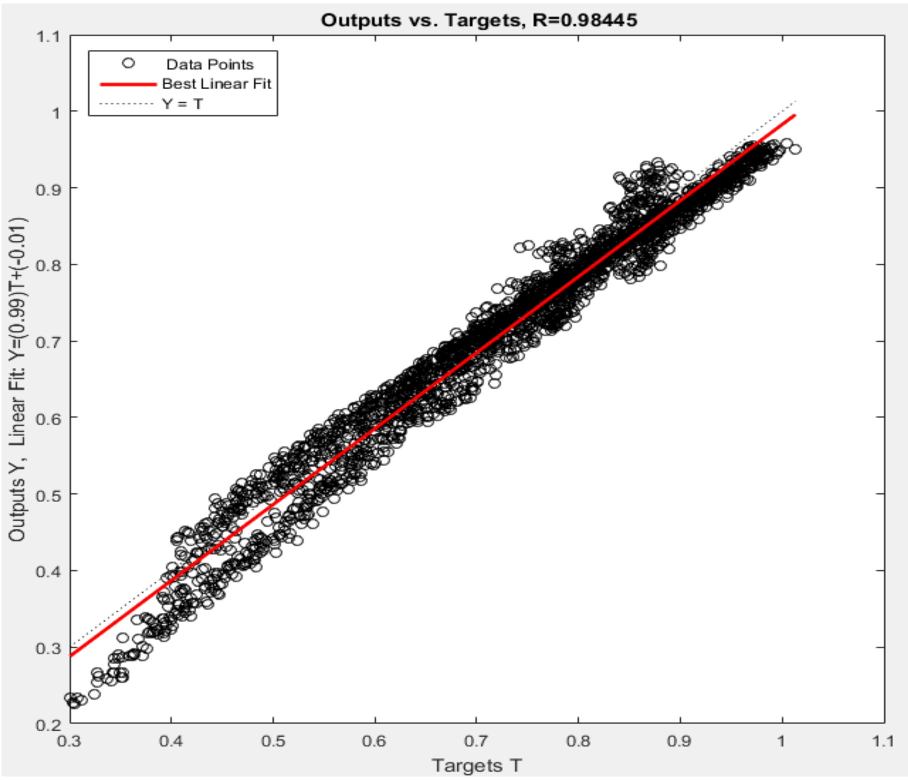

Fig 5.4: Linear Regression of ANN testing

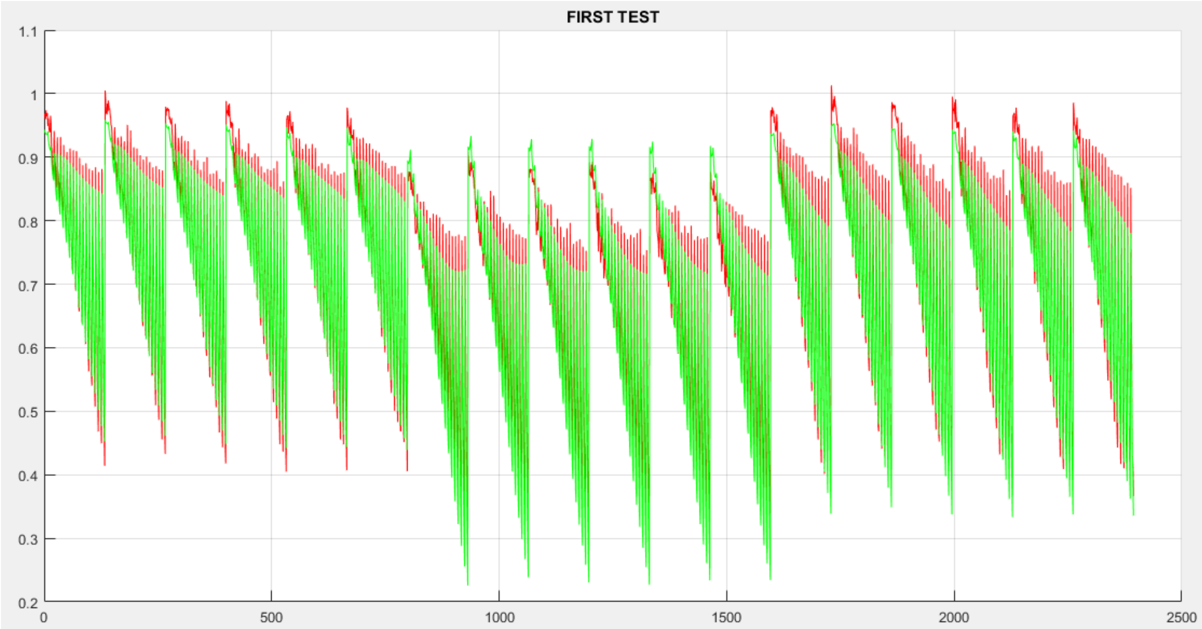

Fig 5.5: Graph of output vs Targets

V.3. Prediction

The trained and tested ANN model was used for 1predicting amplitude reduction ratio for a new set of data. The dataset also consists of six input parameters. The input for prediction contains 6 × 798 data points. These 798 data points consists of all elements for the six parameters. The ANN was simulated with these inputs to predict the corresponding outputs. The output results were satisfactory as they are similar to targets used in the training phase.To validate the prediction of the amplitude reduction ratio, soil parameters used by (Saikia, 2014) E = 46Mpa, ν=0.25 and ρ=1800kg/m³ were among the input parameters for the prediction along with same width, depth and length used for training and testing. (Saikia, 2014) soil parameters were used for validation because the study deal with development of simplified formula for open trench design. The output results obtained strongly agreed to this previous study's. The results from this study are also in agreement with (Alzawi, 2011) and (Jayawardana, 2019) but there is a slight difference which is understandable due the fact that they studied in-filled trench.

After the output was predicted, a graph (Fig 5.5) was plotted to show the output (amplitude reduction ratio and the 798 data points (which correspond to the input parameters). The amplitude reduction ratio (Ar) varied from a highest of 0.31 to lowest of 0.95. Five random amplitude reduction ratios were chosen from the output graph and their corresponding data points were traced. Having these corresponding data points, their inputs parameters were easily located.

To identify the values of these input parameters especially for the trench dimension, there was a need for unnormalizing the inputs to their initial values. The input parameters were converted back to their un-scaled form using:

$$\mathbf{X_i = \frac{1}{2}((X_N)_i) + 1) \times (Xmax - Xmin) + Xmin} \qquad (15)$$

Xi = i^{th} value of an input parameter

$(Xi)_N$ = Normalized value of an input parameter

Xmin = Minimum value of an input parameter

Xmax = Maximum value of an input parameter

To examine the trench parameters for a particular amplitude reduction ratio, Table 5.1 was created to showpredicted trench parameters, amplitude reduction ratios and isolation level.

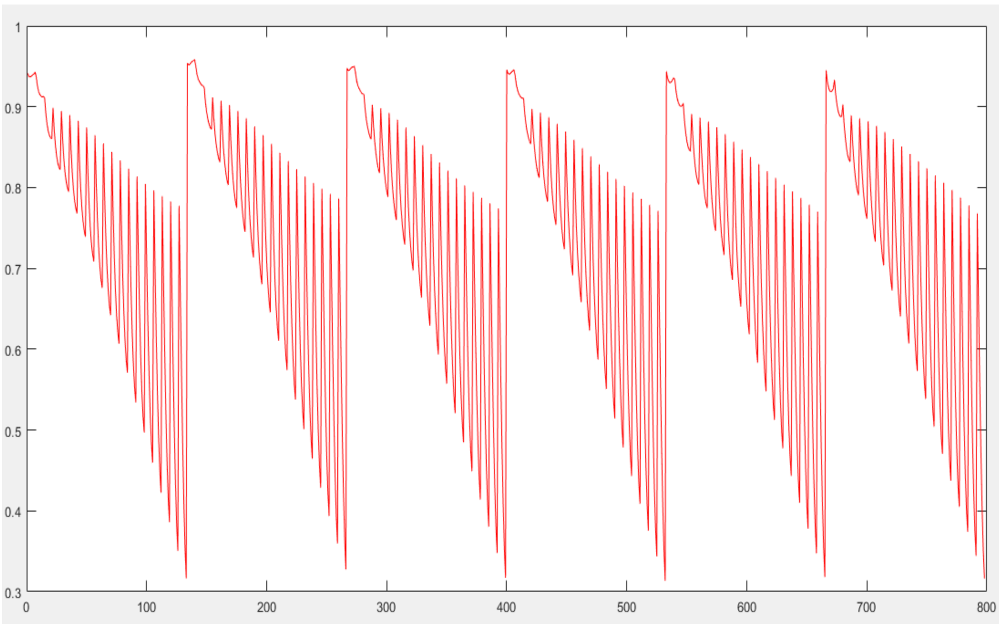

Fig 5.5: Predicted output graph

Table 5.1: Predicted trench parameters, amplitude reduction ratios and isolation level

Amplitude reduction ratio (Ar)	Isolation (100% - Ar)	Trench Width	Trench Depth	Trench Length
0.8071	19.29%	0.5m	3m	20m
0.6069	39.31%	0.5m	6m	20m
0.5709	42.91%	0.5	6.5m	20m
0.3275	67.25%	1m	10m	20m
0.3172	68.28%	1.5m	10m	17.5m

V.4. Conclusion

Based on the results presented in table 5.1, the trench dimensions determine the level of isolation that be attained. The minimum isolation of 19.29% requires a trench configuration of 0.5m wide, 2m deep and 20m long. The average isolation of 42.91% requires a trench configuration of 0.5m wide, 6.5m deep and 20m long. The highest isolation of 68.28% requires a trench configuration with 1.5m width, 10m depth and length of 17.5m.

It can be concluded that the choice of trench configuration depends on two factors:

- The desired level of Isolation
- Limit of reachable trench dimensions; for example, an open trench that shouldn't be more than 8m deep

GENERAL CONCLUSION

Many numerical and experimental research wereconducted in the past two decades to study the vibration isolation using wave barriers and to have an in-depth understanding of vibration isolation. Most of these research mainlyfocused on the development of numerical methods for analysing vibration isolation problems, investigating open trenches, in-filled concrete andwater trenches, sheet-pile walls, and steel piles etc.However, only few studies have explored ANN as a tool for determining trench dimension in the case of open trench. In this thesis, the principles of wave propagation in an elastic soil media and their application to ground vibration isolation by trenches are reviewed. The comprehensive literature reviewshow that application of ANN on vibration isolation is limited. The results obtained agreed with previously published works especially (saikia 2014). Based the results discussions and analyses, the following understandings and conclusions can be made:

1. The considered open trench performed well in reducing the surface waves and the isolation level varies between 19.29% and 68.28%. The highest isolation attained which 68.28% requires a depth of 10m and width of 1.5m.On the other hand, the lowest requires a trench that 0.5m deep, 3m deep and 20m long.

2.The choice of trench configuration depends on two factors; the desired level of isolation and the limit of reachable trench dimensions.

3. The key parameters that influence the trench performance are its depth and the young’s modulus of soil. The soil density, Poisson's ratio, andhave some influence but are not really significant.

4. According to the parametric study in Chapter 4, it can be deduced that trench depth contributed significantly to acceleration reduction. The influence of trench length variation is not really important. The width has a slight contribution but its variation is still essential than the length’s.

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