Structural Damage Detection based on Artificial Neural Network

By

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Submitted in partial fulfilment of the requirements for
the degree of Master of Science in Construction Management
(Civil Engineering)

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City University of Hong Kong

July 2022

DECLARATION

I declare that this dissertation represents my own work, except where due acknowledgement is made, and that it has not been previously included in a thesis, dissertation or report submitted to this University or any other institution for a degree, diploma or other qualification.

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Abstract

Steel construction is a common building material. It has the advantage of being lightweight, durable and recyclable. However, steel structures are subjected to various loads during their service life, in addition to corrosion, high temperatures and buckling. Therefore, the reduction of the resistance strength of steel structures due to various adverse effects is becoming an increasingly important topic.

Non-destructive testing (NDT) techniques are becoming increasingly popular as a defect detection method, with the advantage of not further damaging the component under test. One of the known common NDT methods is based on the vibration characteristics of the structure. The use of vibration-based damage detection methods is widely used to detect, locate, classify and quantify potential damage in structures.

Damage detection of I-beams based on artificial neural networks is the main objective of this study. The study focuses on modeling and modal analysis by the finite element software ANSYS to obtain the natural frequencies of I-beams at different damage levels and damage locations, and to study the dynamic characteristics of each damage in order to evaluate the sensitivity of the modal parameters (natural frequencies) to the steel beam.

In addition to the above contributions in this study, the feedforward back propagation neural grid (FFBPNN), which is built using MATLAB software, is one of the focuses of this study. The extracted natural frequencies are fed to the ANN as input, while the structural damage degree and structural damage location are classified as output to train the neural network. The final results show excellent results for damage identification at four different damage locations. The performance of the network was measured independently using an untested test set, and the results obtained indicate that the artificial neural network algorithm is able to predict the degree of structural damage at different locations well.

Dedication

This thesis is dedicated to my parents and sister for their hard work, continuous support, and encouragement.

In particular, I would like to thank my supervisor Dr. Paul Lam for his guidance and Ren ZhiCheng for his selfless help, without them, I could not have completed this thesis.

I thank you all from the bottom of my heart.

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1. Introduction

1.1. Overview

Steel constructions, one of the most extensively used construction materials today, are structurally solid, have a high strength-to-weight ratio, and are exceptionally resilient. Early in the 20th century, steel constructions were popular, and during World War II, steel was widely employed for military shelters and oil storage. Following the war, steel became more accessible and the industry norm. Some of the world's most recognizable buildings, such as the Empire State Building, were constructed with steel as a primary structural component. Nonetheless, when steel structures are subjected to harsh conditions, the resilience of the structure can be decreased by factors such as poor original design, compromised quality control, inadequate maintenance, or absence of maintenance. Moreover, corrosion and fire may inflict irreparable damage to steel structures. Therefore, researchers must continually comprehend the alterations in the natural features of structural damage in order to mitigate its negative effects. To decrease human deaths and economic losses resulting from circumstances such as pain, failure, damage, and rapid collapse.

Due to China's tremendous economic growth over the past four decades, the country's building sector has achieved amazing success. Nonetheless, this has led to the issue of aging building structures. Since the expense of rebuilding all aged structures is expensive, the application of healthcare monitoring and structural integrity evaluation to ensure structural dependability and public safety would be an acceptable alternative. Existing structural components would need to be evaluated thoroughly to discover flaws and highlight common dangers. Then, a determination is made as to whether the structure must be retested to enhance its consistency and robustness in order to assure resilience, endurance, and security, or whether they must be changed. The fundamental purpose of structural health testing is to extend the life of a structure by reinforcing and repairing the original structure in order to achieve economic balance.

Techniques for detecting non-destructive damage in construction management include radiographic, visual inspection, thermal field and eddy current, ultrasonic or acoustic methods. Magnetic field methods. However, most of these methods are limited by the following two conditions. First, it must be possible to roughly predict the location of the damage. Second, the location to be inspected must be easily accessible. For structures that can be damaged just on the surface of the structure and for which the location of the damage can be roughly determined, several of the above experimental methods can be applied. However, for structures where the location of the damage is unknown and for large structures, the above methods are not applicable.

Therefore, researchers have proposed a vibration-based damage identification technique to overcome the shortcomings of these experimental methods. This method allows the condition of the entire structure to be evaluated in one pass. Defects alter the structure's physical attributes (such as stiffness and mass) and dynamics properties (such as frequency response function (FRF), natural frequency, damping ratio, and vibration mode). Consequently, any flaw, such as its position and severity, may be detected by studying the dynamic features of the structure derived from structural vibrations or, more particularly, by vibration-based damage detection methods.

1.2. Problem Definition of the Study

Over the past few years, numerous technical studies on condition monitoring have been published. There are two widely employed types of damage identification procedures. They are, respectively, local and global approaches. The local approach relates to direct visual assessment or research approaches like ultra-sonic, radiographic, eddy current, and magnetic particle testing. The local technique is limited by the necessity to forecast the location of structural deterioration. Therefore, it is not necessary to forecast the location of structural damage when using vibration-based global approaches to assess structural damage. There are a variety of vibration-based approaches used to identify, localize, and quantify damage in structures, according to available publications in the technical literature.

Modal parameter-based vibrating damage detection methods are among the most prevalent vibration damage detection approaches. It is claimed that there is no adequate approach for using vibration data to detect, locate, and estimate the extent of the damage in a building. In addition, no method for the thorough identification of any fault in any structure has been given (Wenzel, 2009). The development of damage detection and localization methods relying on reaction monitoring information of in-service structures continues to be difficult. Consequently, the introduction of all such detection methods will enable more precise assessments of the life span of structures (Friswell, 2007).

It is important to note that fluctuations in resonance frequency alone may not be adequate for integrity surveillance. Secondly, in the implementation of the suggested approach for damage identification, some researchers favor the intrinsic frequency as the most significant indication for recognizing and assessing the degree of structural damage. Others, however, believe that the modal damping ratio is an excellent predictor of deterioration. Detecting damage and evaluating the status of the soil-wood structure is crucial, particularly when the building is old or overloaded. Unknown is the history of numerous types of geotechnical constructions. It's some other troublesome barrier to the application of resonance-based monitoring systems in geotechnical constructions. Consequently, information from actual building models are frequently unavailable. Consequently, the use of commercial software to estimate the numerical model of the initial intact condition will serve as a reference for the final comparison of the measured values' deviance.

In this study, the numerical findings may be utilized as inputs for training an artificial neural network to pinpoint the position and degree of damage. Thus, the suggested approach for damage detection and condition evaluation closes the knowledge gap and improves the dependability and usability of the structural diagnostic system based on the mythological neural grid.

1.3. Aim and Objectives of the Study

This study's primary purpose is to examine the application of experimental modal analysis on steel beams and to estimate the degree and location of structural damage in steel beams. In addition, the Myoga Neural Network is utilized to anticipate the location and severity of damage to the steel beam. To accomplish this purpose, the procedures listed below must be taken.

1- To analyze the behavior of steel beams, modal parameters (natural frequencies, dampening ratios, and modal shape) are extracted.

2- The effects of different degrees of cracks and damage at different locations on the steel beam are investigated.

3- An artificial neural network (ANN) is introduced to predict the location of structural damage and the degree of structural damage, and a test set is used to verify the accuracy of the predictions of this ANN model.

2. Literature Review

2.1. Structural Health Monitoring

Infrastructure that has been used, such as bridges, structures, and other structures, has a direct effect on our everyday life. It is the lifeblood of social and economic activities and a vital component of human welfare. The majority of the current infrastructure is still in use, however in certain countries, particularly emerging nations, there is an accumulation of aging and infrastructure-related defects. Therefore, it is essential to examine the state of these sorts of buildings, particularly after natural or man-made catastrophes (such as earthquakes) (such as explosions or fires). In order to avoid or mitigate the effects of natural catastrophes and expedite recovery, it is crucial for society to monitor the state of these buildings and repair them as soon as necessary.

Structural health monitoring is an emerging technology that enables the detection, measurement, and documenting of changes impacting the performance of structures in order to enhance their safety and maintainability. SHM technology is often utilized to identify indications of accidents, abnormalities, degradation, and faults via reactions that may impact the availability and safety of a building. SHM technology is commonly utilized to identify signs of accidents, abnormalities, degradation, and faults that may compromise the usage and safety of buildings. For instance, a structure's reaction must be a function of acceleration, strain, and other elements. For instance, a structure's reaction must include acceleration, strain, deformation, environmental influences (humidity, temperature, and pressure), and other structural parameters (Dong et al, 2010). Depending on the state of the building, several safeguards may be taken. Knowledge of the structure's state enables specific actions to be taken to prolong the structure's useful life and avoid unforeseen catastrophic breakdowns. The state of the building permits preventative steps to be taken to prolong its useful life and avoid catastrophic breakdowns from happening unexpectedly. Detection techniques for anomalies, degradation, and failure may eventually lower life-cycle costs. Consequently, the majority of developed nations are preparing to boost their SHM expenditures for their main utility systems. Prior to the accumulation of serial damage, the integrity and resilience of structural components should be enhanced to prevent more costly repairs (Gassman and Tawhed, 2004).

SHM is important to note that some circumstances may potentially constitute structural damage. Examples of damage include modifications to substances, linkages, and initial conditions.

Changes in materials, connections, and boundary conditions, for instance, might be considered damage since they can result in a decline in structural performance (Gao and Spencer, 2008). In addition to aging, erosion, and regular activities, ocean waves may cause damage to building structures. Waterborne wave loads, spalling, and corrosion may cause damage to offshore structures. In addition to the construction of the building In addition to the building structure, bridges are also exposed to vehicular traffic, combustible loads, and other environmental factors. In addition, earthquakes, storms, and cyclones may cause structural damage due to their enormous loads. Moreover, extreme stresses from earthquakes, hurricanes, and cyclones may cause mild to serious structural damage (Sundaram et al., 2013).

SHM may use a range of non-destructive damage identification equipment, techniques, and systems. These techniques may be categorized as nondestructive evaluation (NDE), local damage identification and nondestructive detection (NDT), and global damage identification (GDI) (Doebling et al., 1998). The authors state that local damage detection techniques, such as visual examination, ultrasonic methods, and X-rays, are used to diagnose damage and evaluate the structural integrity of buildings. These procedures often need previous knowledge of the defect's area and are readily testable, which cannot be guaranteed in the majority of instances throughout the soil building process. To circumvent these obstacles, global damage detection approaches, such as vibration-based damage identification systems, have been developed.

SHM systems generally have the following components: sensor and information gathering grid; data transmission; information processing; information storage; diagnostics and prognosis analysis (damage identification and modelling methods, event identification, and interpretation); and information retrieval (Büyüköztürk and Yu, 2003; Bisby, 2006).

2.2. Damage Detection

Damage identification of buildings is often cited as one of SHM's essential components. A change in the structural qualities of a structure owing to a weakness is termed as damage. Changes inside a structural system have a detrimental effect on the system's present and future performance. Without comparing two conditions of the same system, one of which is undamaged and the other of which is damaged, damage has no actual significance (Sohn et al., 2004). Consequently, a comparison of these two states will identify any decline owing to damage or other vulnerabilities. For instance, the development of fractures in a structure might result in changes to its stiffness. As stiffness is decreased, the system's dynamic behavior changes. Changes in physical qualities (mass, stiffness, and damping) and their modal properties resulting from defects (inherent frequency, damping ratio of the structure, and vibration mode). The loss in stiffness is dependent on both the size and location of the flaw. Detecting damage in structural systems thus needs identifying the location and estimating the amount of the damage. In recent years, the employment of various nondestructive approaches for damage detection has received a great deal of attention. Damage detection in structural systems necessitates determining the location and amount of the damage. Early damage detection techniques in structures are crucial for preventing unexpected architectural component failure (Sinou, 2009).

2.3. Damage Simulation Techniques

Methods for stimulating damage are utilized in the area of detection of damage based on vibration Methods, and Dimarogonas (1996) and Ostachowicz and Krawczuk provide a complete assessment of damage/crack simulation approaches (2001). Several main kinds of damage simulation approaches have been identified and are frequently utilized by scientists.

Friswell (2007) provides three unique approaches for damage modeling, including reduction of local stiffness, discrete spring components, and complex models in two or three dimensions. The strategy for reducing local stiffness may be applied in several ways. Therefore, it is the most straightforward of the three distinct simulation methodologies. Local stiffness may be decreased by introducing a missing damage or by decreasing the faceted second-order moment (I) or the modulus of Young (E).

Ovoráby et al. (2003) employed a flawed approach for simulating damage by thin sawing. In their experimental work, the scientists intended to use frequency and amplitude to identify fractures in aluminum beams. Similar methods were utilized via Dackermann et al. in a multi-storied building (2011). The response of frequency function was considered as one of the input variables the human neural network in order to determine the location and degree of injury. The human neural grid uses the frequency response function as an input parameter to determine the location and degree of injury. Theoretically, the ANSYS program was utilized to generate faulty damage with varying severity and location. Theoretically, ANSYS software was utilized to develop a numerical model of a complicated two-story frame structure with faulty damage of varying locations and severity, which was then examined under ambient vibration. The analysis was conducted when vibrations were present. The results demonstrate that the suggested algorithm can effectively and dependably detect damage in complicated multi-story constructions.

In addition, the FEM software SAP2000 was used to simulate steel beams and plates. (2009) Steel beam and plate modeling using the finite element software SAP2000. On previously tested beams, single and multiple defects of two different sizes (10 millimeter x 5 millimeter and 20 millimeter x 5 millimeter (length x depth)) were simulated by removing chosen damaged components from the bottom of the beam in the finite element model. on the basis of the research by Cornwell et al. (1999), their damage modeling approach simulates the reduction in stiffness caused by decreasing the flexural stiffness of a structure. Plate construction was separated into two oriented components. In the first and second examples of this investigation, there was a decrease in stiffness of 25% and 10%, correspondingly. Based on the results, the algorithm can detect locations with stiffness decreases of less than 10 percent using only a few modes of measurement.

For the purpose of monitoring the structural health of bridges, Zhou (2006) investigated mechanical vibrations as damage detection approaches. (2006) performed an experimental investigation on vibration-based damage detection technology for monitoring bridge structural health. In the upper portion of a bridge apron with a short span, little damage was incurred. In physical bridge systems, the damage consisted of the removal of a 100 millimeter by 100 millimeter by 25 millimeter concrete structure from the bridge's surface. The deck surface was progressively compromised in nine distinct spots. The experimental work included determining the dynamic The studies included calculating the dynamic characteristics of the whole system, then progressively generating new damage states and identifying the attributes associated with each condition. Five non-model vibration-based damage detection approaches are adequate to identify and localize damage to simply supported decks or bridges, according to the study's findings.

Wang (2010) did experimental research on crack damage employing both sawing damage and honeycomb damage. Damage. The degree of the damage cautilized to the reinforced concrete beams was graded into three levels: mild, moderate, and severe. Sawing has cautilized the damage. The mild damage has a length of 5 mm and a depth of 50 mm. The cutouts for moderate and severe damage are, respectively, 5 mm × 100 mm and 5 mm × 150 mm. In this instance, the fractures are positioned at 1/4, 3/8, and 1/2 of the beam's span. In the instance of honeycomb damage, the casting process with dimensions of 89 mm (long) × 75 mm (wide) × 1.5 mm created the damage (width). During the casting process, the concrete was replaced with a polyethylene hexagonal block measuring 89 mm (long) × 75 mm (width) × 100 mm (height). Honeycomb The damage was situated at three-quarters of the reinforced soil beam's span. The objective of this project was to find the damage and determine its severity on the basis of the vibration pattern's curvature and vibration pattern's pattern. On the basis of the combination of vibration pattern and curvature, the goal of this project is to find the damage and assess its severity. The suggested technique can detect the site of the damage and measure its severity with high confidence.

2.4. Non-destructive Damage Detection Techniques

Because unplanned structure collapse may cause catastrophic financial losses and human deaths, the scientific and technological communities are growing more interested in structural damage detection Methods. Since inadvertent structural collapse may lead to catastrophic financial losses and deaths, the scientific and technological communities are growing more interested in damage detection devices for structures. The security and structural stability of structures should be preserved via the use of dependable and effective non-destructive damage identification Methods. Methods for recognizing damage precisely are important for preserving the architectural integrity and security of structures. Local or worldwide Methods to damage detection are two types of non-destructive damage assessment (Doebling et al., 2004). As previously described, the ultrasonic approach and the X-ray technique are two examples of local damage detection Methods. A dynamic vibration-based approach is an example of an approach used throughout the world to identify damage.

As a consequence of the inadequacies of the localized damage detection technique, a great deal of research and development has been devoted to the worldwide approach to damage identification. This is because local damage detection approaches need that the damage's surrounds be known before to its discovery and that the damage's position be easily accessible. However, until the damage is identified and its location is inaccessible, it cannot be repaired. The site of the damage may not always be approachable, and information on the damage is not always readily available until the harm is identified. As a consequence, methods for worldwide inspections have been developed to not only detect known damage but also pinpoint its location. Thus, worldwide inspection approaches have been developed not only to detect concealed and unreachable damage, but also to help in the study of such damage in complex structures.

In the last ten years, vibration-based damage detection approaches have garnered the most attention due to their advantages, notably their usability. Frequently, these strategies rely on the premise that dynamic features, such as modal frequency, modal shape, and modal damping, are inversely related to structural rigidity (Ruevskis et al., 2009). Consequently, a reduction in stiffness is inferred by the change in dynamic properties.

These two categories include model-based and non-model-based vibration-based damage detection approaches (Farrar and Doebling 1997; Huang et al., 2012). In contrast, Lee et al. (2004) categorize vibration-based damage identification approaches into four basic types, each using a unique set of features for damage detection. The damage recognition methods of Bakhary (2008) can be divided into three groups: direct approaches, modeling update approaches, and approaches based on artificial neural networks. According to Wang (2010), these methods can be classified into three primary categories: vibration-based Methods, Methods on the basis of human intelligence, and methods on the basis of microwave analysis.

Table 2.1: Damage detection categories and methods as proposed by Lee, et al., 2004).

Category		Methodology
Modal Parameters	Natural Frequencies	Frequency changes
		Residual force optimisation
	Mode shapes	Mode shape changes
		Modal strain energy
		Mode shape derivatives
Matrix Methods	Stiffness-based	Optimisation technique
		Model updating
	Flexibility-based	Dynamically measured flexibility
Machine learning	Genetic Algorithm	Stiffness parameter optimisation
		Minimisation of the objective function
	Artificial Neural Network	Back propagation network training
		Time delay neural network
		Neural network systems identification with neural network damage detection
Other techniques		Time history analysis
		Evaluation of FRFs

2.4.1. Modal Parameters Based Technique

The fundamental frequencies and its associated fundamental properties, including the vibrating pattern and fundamental dampening, are essential for defining the overall assessment of the dynamic behavior of the selected structure. Since their values and variations reveal changes in the building's physical properties (weight, dampening, and stiffness) and boundary conditions, modal parameters are vital for classifying structures as per their characteristics (Farrar et al., 2001; Owen and Pearson, 2004). As per Chen et al. (1995), among some of the physical parameters, structural stiffness variation affects the construction's appropriateness and safety. In vibration research, the most often utilized modal parameters for damage diagnostics are fundamental frequencies and fundamental vibrating mode (Hearn and Tesa, 1991).

2.4.1.1. Natural Frequency Based Method

The earliest and most prevalent approach for determining the presence of defects in a structure is the selection of natural frequencies. This strategy's use has been constrained for several reasons. First, a single transducer is sufficient for a range of functions, including determining the mode shape and intrinsic frequency of a structure. For a number of applications, the intrinsic frequencies may be easily estimated or even predicted from a single accessible location on the structure utilizing a single sensor. Therefore, the use of intrinsic frequencies is an effective way for identifying damage or defects. As a consequence, the use of intrinsic frequencies as a method of damage or defect identification is both straightforward and cost-effective. Second, experimental noise has less of an effect on natural frequencies in general. Corrosion, deteriorating, delamination, and debonding could substantially alter the intrinsic frequency of a structure if they are present (Saline) (Salawu, 1997). The inherent frequency of a damaged/undamaged structure of a given size is mostly determined by the system's stiffness. It is feasible to determine the comparable elastic modulus of a structure given its diameter and gravitational force. For a given structural moment of inertia, the structure's associated modulus of elasticity may be determined. In other words, altering the intrinsic frequency is the essential element of structural damage detection.

Early studies on natural frequency changes focutilized mostly on the most fundamental structural components (Adams et al., 1978). 1979 saw the release of one of the most cited works on the use of natural frequencies in damage detection, published by Cawley and Adams. (Adams et al., 1978). Cawley and Adams published in 1979 one of the most cited publications on the use of natural frequency shifts in damage identification. They addressed the use of frequency shifts to pinpoint the location of damage in a structure. They explored the use of frequency shifts to detect and quantify damage at particular locations inside the structure. Since then, several studies on the use of frequency shifts for damage detection have been published; Salawu (1997) and Doebling et al. review a considerable body of research on this topic (1998).

Nevertheless, for whatever reason, it is not always possible to determine damage using intrinsic frequencies. Methodology The primary problem of the approach is that it requires very precise measurements of the damage produced by low frequencies (Doebling et al., 1998). The intrinsic frequency may be affected by environmental changes, a second disadvantage (e.g., temperature or humidity). Therefore, measurement mistakes may hinder the identification of exceedingly minute frequency fluctuations. Estimations on the basis ofly on natural frequency may lead to imprecise damage detection (Maeck and De Roeck, 2002). It is recommended, therefore, to apply approaches other than natural frequency shifts to improve damage detection. Utilizing approaches other than inherent frequency fluctuation is thus recommended to improve damage detection capability.

2.4.1.2. Brief History of Neural Networks

The effort to represent neurons may be seen as the first stage toward the development of a human brain network. First model of a neuron was created by a neurologist. A neurologist and a young mathematician, McCulloch and Pitts, created the first models of neurons (1943). The duo McDonald and Pitts (1943). They released a research on the functioning of McCulloch-Pitts neurons. A model was developed using one output and two inputs. The disadvantage of the model is that the weights of each input are set, preventing it from learning from examples, which is a problem with ANNs. This is a fundamental component of ANN Methods (Kumar, 2014). This notion of neurons was bolstered by Hebb (1949), who developed a learning approach for altering connection weights, such as "Fn. Hebb (1949), who also created a learning mechanism for altering connection weights, elaborated on this concept in his book Organization of Behavior. It should be emphasized that Herb's law is an essential learning notion in the area of neural networks. It should be emphasized that Herb's law is an essential learning concept in the area of neural networks. Rochester, an IBM Research Labs employee, devised neural grid simulation with an emphasis on using computers. Rosenblatt (1958) proposed the perceptual model as the first of its kind. The weights of the perceptual model may be Widrow and Hoff (1960) proposed the ADALINE (ADAptive Learning) grid paradigm for computational components. The model is not their only concern. Along with the model, they recommended the LMS (Least Mean Square) learning approach for adjusting the model's weights. Although the Perception and ADALINE models are conceptually similar, ADALINE's transfer function is different. In addition to a clear notion, Hopfield (1982) produced a useful tool. Through mathematical research, a particular kind of recurrent neural grid (Hopfield's grid) was described. It was shown via mathematical study how the Hopfield grid operates. In addition to illustrating how these networks operate, their usefulness is well acknowledged. Therefore So, at that very moment, something occurred that was primarily responsible for the rebirth of the legendary neural network. Rummelhart et al. (1986) announced the invention of a system for learning in which the weights of a multilayer feedforward neural grid are modified automatically. By meticulously altering the weights of a multilayer feedforward neural grid, (1986) disclosed the discovery of a way to learn an implicit mapping between pairs of input and output patterns. Due to the LMS rule, back propagation of errors, a process for learning laws, occurs. From November 21 to 24, 1987, the Institute of Electrical and Electronics Engineers organized the first International Conference on Neural

Networks in San Diego, California. Adeli and Yeh published the first journal article on the use of neural networks to geotechnical engineering in Computer-Aided Civil and Infrastructure Engineering (1989). Since then, several articles on the use of neural grids to soil engineering have been published. In addition to geotechnical engineering, the progress of neural networks has garnered broad interest in a range of scientific disciplines.

2.4.1.3. Artificial Neural Network Based Methods

Due to their impact on a structure's durability, the presence and severity of flaws must be considered one of the most important structural characteristics. This could be utilized to estimate the longevity of a building. This often requires extensive structural model information, which is not always attainable. The study of neurons or neural cell clusters gave birth to the ANN, which has subsequently evolved into a potent tool for pattern recognition, classification, and fault detection in structural systems. It has evolved as one of the most effective computer models for classifying, recognizing, and detecting structural system patterns (Pandey and Barai 1994).

Multilayer perceptron trained by backpropagation Methods and its competitor pair, the radial basis function, are the most utilized neural grid designs (Bishop, 1995). Additional information about ANN Methods and characteristics may be found in (Bishop, 2006). Adeli conducted a comprehensive analysis and overview of the use of the human brain network in the implementation of the soil soil process (2001).

In a study by Kudva et al. (1991), the MLP neural network identifies damage on a plate by applying a static uniaxial strain to the structure. The neural grid took strain gauge data as input, and produced the location and size of the holes as output. Using a variety of hole sizes to imitate deterioration. Despite difficulties in predicting the size of the holes, the neural grid was able to predict the error location prior to the failure, as demonstrated by the data. The neural grid accurately determined the size of a hole. This is because the strain measurements do not offer a clear indication of the location and magnitude of the damage.

Wu et al. (1992) released the first academic article to detect damage to dynamic parameters using the MLP neural grid to detect damage in a three-story structure model. To reflect the damage, the stiffness of the members was lowered from 50 percent to 75 percent. The frequency response function of the acceleration data between 0 and 20 Hz is utilized as the input vector, while the two-digit digits 1 and 0 are utilized as the output to indicate the amount of damage, damage, and undamaged condition of each member in the simulated three-story structure. The grid can identify damage with a 25 percent degree of precision.

Walden et al. (1993) utilized the MLP neural network to classify experimental frame constructions as damaged or undamaged. There were discovered twenty binary number representations of membership hierarchies. There were discovered twenty binary number representations of membership hierarchies.

In the subsequent study, Mythology et al. (1996) employed back-propagation ANNs to detect changes in structural system characteristics. The model was taught to identify both linear and nonlinear autonomous single anomalies. Also of concern is the efficiency of the inspection grid at varying vibration levels. In order to monitor the structure's health, the grid is trained using identical vibration measurements of the same structure obtained under different conditions. Inputs to the grid are relative velocity and displacement, and its output is power restoration. Even when vibration data are contaminated by noise, this approach can still identify changes in structural qualities, as shown by the results. In addition, it is shown that using longer vibration characteristics as inputs improves training grid and prediction performance. In other words, providing the grid with more training data may result in more accurate predictions for the test data. However, there are no regulations specifying the optimal duration of vibration characteristics to use for training and assessment. Experimentally, Masri et al. (2000) applied this method to nonlinear multi-degree autonomous systems. There are no defined guidelines for the appropriate length of vibration characteristics for training and evaluation. Masri et al. (2000) experimentally expanded this method to nonlinear multidegree systems. There are no defined guidelines for the appropriate length of vibration characteristics for training and evaluation. Masri et al. (2000) experimentally expanded this method to nonlinear multiple autonomy systems.

They utilized principal component analysis to reduce the size of the frequency response function as an input variable to the artificial neural network rather of using full-size, despite the fact that Zang and Imregun (2001a) recommended a variety of methods for doing so. The actual condition of the railway wheels, whether sound or damaged, is predicted by the ANN model's output. The 4096 spectral lines in the raw FRF data are grouped along the x, y, and z axes with a compression ratio of around 400 in each direction. Twenty compressed FRF instances are utilized for testing, whereas eighty FRF samples are employed to train three distinct ANN models, each of which corresponds to a coordinate direction. The results indicated that all occurrences of injury could be accurately classified as either damaged or healthy. In a 2001b publication, Zang and Imregun described the use of FRF to estimate the degree and location of damage.

According to Nguyen et al. (2015), the concrete arch of the replica of the Sydney Harbour Bridge has deteriorated. The methodology was verified using numerical simulations and large-scale laboratory investigations. Using the impact test technique for the damage scenario, acceleration measurements were conducted to produce residual frequency response functions. Using PCA, these data were then reduced to smaller sizes. The specimen is treated to localized damage using four various harm cutting degrees (damage severity). The numerical study was conducted using commercial ANSYS software. To duplicate the experimental scenario, a numerical model was utilized, and additional instances of damage were included. A few samples of damage were utilized to train the ANNs. After training ANNs on a small fraction of the damage cases, the model was validated using the remaining damage examples. The ANN output is meant to convey the severity (damage severity) of the damage reductions. According to experimental results, the test case may be interpolated in a training case using compressed FRF data from the Sydney Harbour Bridge. In addition, a numerical model was constructed to offer more instances of damage for the training of the ANN model. The interpolation capabilities of the model was found to be enhanced by training the ANN model with more instances of damage, which allowed the model to more correctly represent the relationship between the grid's input and output.

3. Theory of Modal Analysis

3.1. Introduction

Modal analysis is a method for analyzing the dynamic properties of a structure, including its natural frequencies, damping ratios, and modal shapes. It often combines the experimental technique with the finite element simulation method, as detailed below. Finite element analysis may be utilized as a stand-alone or supplementary method, often when speed is required, the cost of the experiment is high, or the experiment cannot be repeated. Only experimental modal analysis, also known as modal testing, provides insight into the dynamic characteristics of a structure in real-world conditions. FEA is utilized to create model parameters and verify the correctness of simulation and experiment. It emphasizes the relationship between physics and mathematics.

As stated earlier, modal analysis is a technique that combines experimental and theoretical analysis to study the dynamic behavior of a structure in terms of modal characteristics such as those mentioned below. First, natural frequencies show the amount of an object's oscillation when no external stresses are present. This function is influenced by stiffness and mass. Second, each mode shape is related to the structural deformation and natural frequency. The ultimate goal of the damping factor is to dissipate energy and permit a gradual decrease in the amplitude of the vibration.

Thus, modal analysis is an indispensable tool for comprehending the relationship between experimental and analytical models. These strategies can be utilized in the area of vibration to estimate vibration behavior, identify and assess structural damage, evaluate structural robustness, modify and revise models, develop experimentally based models, and test design-based models.

3.2. Structural Dynamic Characteristics

In general, three models may be utilized to depict the dynamic aspects of a structure: the spatial model, the modal model, and the response model. The first phase of vibration analysis is the spatial model, which is defined by mass, damping, and stiffness and utilized to represent the physical attributes of the structure. Modal analysis is the second stage of vibration analysis. The modal model is utilized to represent the oscillation characteristics of the structure in the absence of any external stimulation, including the natural frequencies, modal shapes, and modal damping coefficients. The third level of vibration analysis is described by the response model. This phase depicts the structure's exposure to external stimuli. In this situation, the structure's vibration depends not only on its intrinsic properties, but also on the kind and magnitude of the created forces.

Although these three topics are presented differently, they are essentially related. Figures 3.1, 3.2, and 3.3 depict the interrelationships of the spatial, modal, and response models, respectively. The spatial representation of the structure is given by the structure's physical properties, namely the mass [M], damping [C], and stiffness [K] matrices, each of which has a size of N N. The modal model consists of an assortment of modal parameters with N natural frequencies (r), N modal damping ratios (r), and N vibration mode shape vectors (r). Response model is the vibration mode of the structure for a certain time- or frequency-dependent response function. A response in the form of a frequency response function or impulse response function is an example of a temporal reaction.

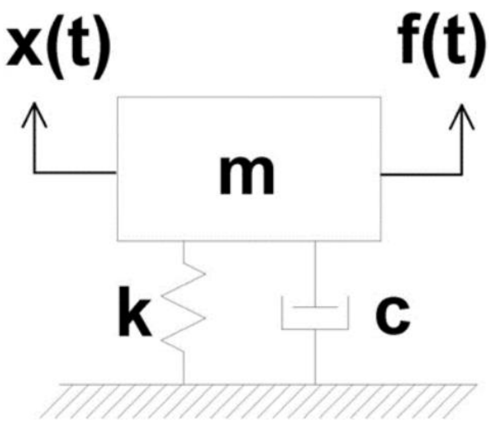


Figure 3.1: Spatial Model of a structural system (Avitable, 2012).

where:

[M]	is mass matrix
[K]	is stiffness matrix
[C]	is viscous damping or structural (hysteretic) damping matrix

Matrices have NxN dimensions; N is number of degrees of freedom and is equal to number of equations of motion.

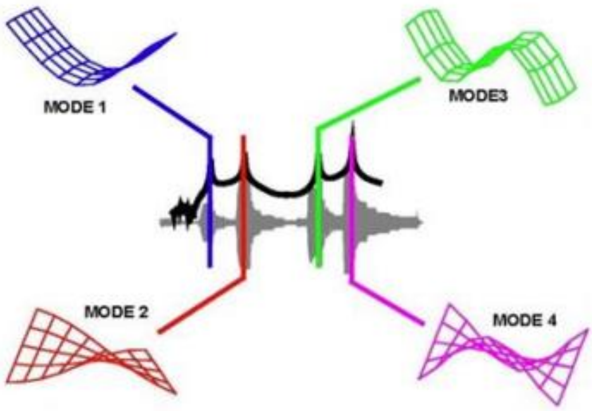


Figure 3.2: Modal Model of a structural system (Avitable, 2012).

where:

(ωr) is natural frequency

(ζ_r) is modal damping ratios

{φr} is vibration mode shape vectors

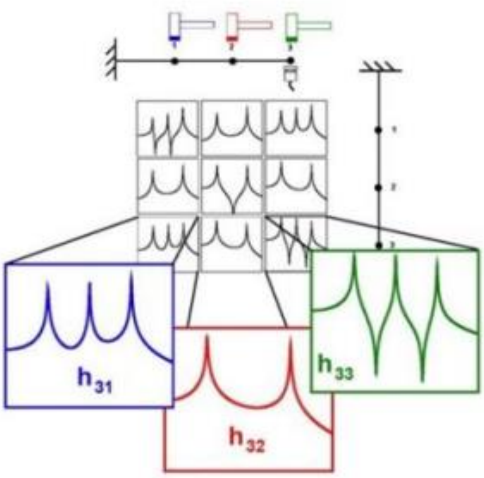


Figure 3.3: Response Model of a structural system (Avitable, 2012).

where:

[$H(\omega)$] is matrix of frequency response functions (FRF)s, in terms of Receptance, mobility and accelerance. Or it is impulse response functions (IRFs)

3.3. Theoretical Routes

In the extended theoretical route illustrated in Figure 3.4, the stiffness [K], damping [C], and mass matrix [M] of the structure, also termed as the spatial model, may be included into a description of the physical properties of a structure (structural model). By combining the structure's stiffness [K], damping [C], and mass matrix [M], also termed as the spatial model, the structure's physical properties may be defined (structural model). Using the eigenvalue problem, one may compute the modal model from the spatial model and obtain the theoretical modal analysis. In the last step, the response model, which can be derived from the modal model via transfer functions, will be shown.

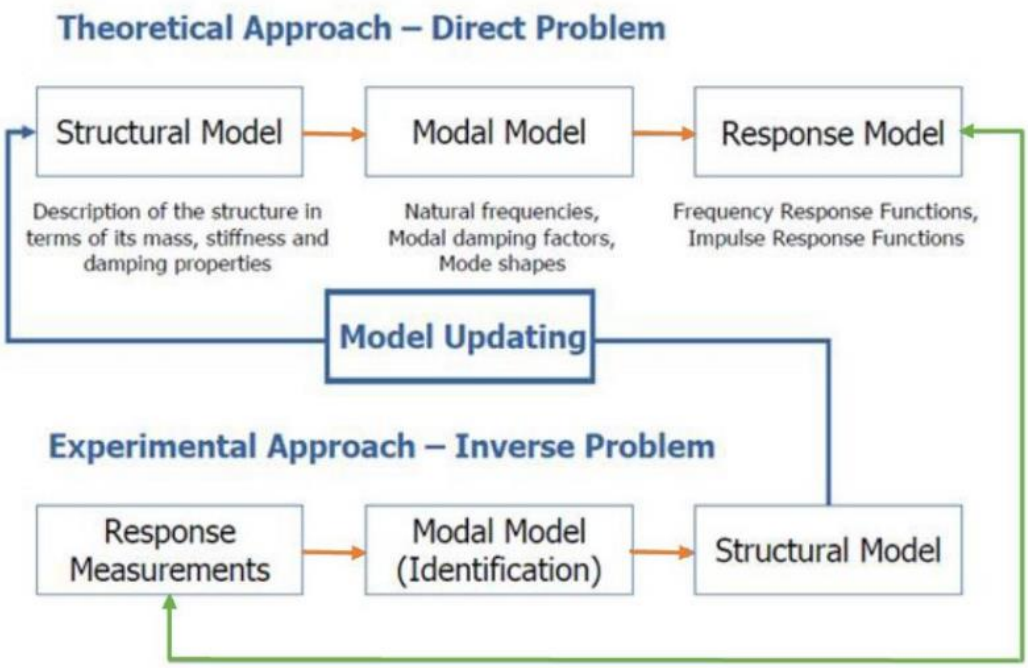


Figure 3.4: Interrelation between the various types of models in theoretical and experimental routes (after Golinval, 2009).

In contrast, the experimental method, also known as modal testing, begins with a lab-based structural test employing the configuration seen in Figure 3.4. Using specialized software to evaluate the data of monitoring the structure's response to a known stimulus, the response model may be built. This modeling technique incorporates the bulk of the fascinating information about the system's reaction and displays it as FRF. The FRF is too complex to be shown accurately in a single two-dimensional figure. It could be displayed in several ways, each of which serves a distinct function. The modal model could then be derived from the experimental data using modal parameter estimation Methods. The spatial model could also be retrieved from the modal model and modal parameters via coordinate transformation. In order to conclude this approach, the relationships between the structural matrix and the modal parameters, as given in Equation (3.1), may be shown (Ewin 2000).

$$[K] = \sum_{r=1}^{N} \{\phi\}_r^{-T} [\omega_r^2] \{\phi\}_r^{-1} \tag{3.1}$$

where:

$\{\phi\}_r$ is mode shape vector

ω is natural circular frequency

3.4. Multiple Degrees of Freedom System

More masses, springs, and dampers enhance the mathematical formulation's complexity. Continuous structural process systems are more sophisticated than single-degree-of-freedom systems because they have an endless number of degrees of freedom (single-mass, spring, and damper systems). Consequently, the general example of multi-degree-of-freedom systems will be utilized to illustrate the link between the frequency response function of the structure and the modal vector of the predicted structure. Figure 3.5 depicts a three-level, single-compartment frame structure with an infinite number of degrees of freedom.

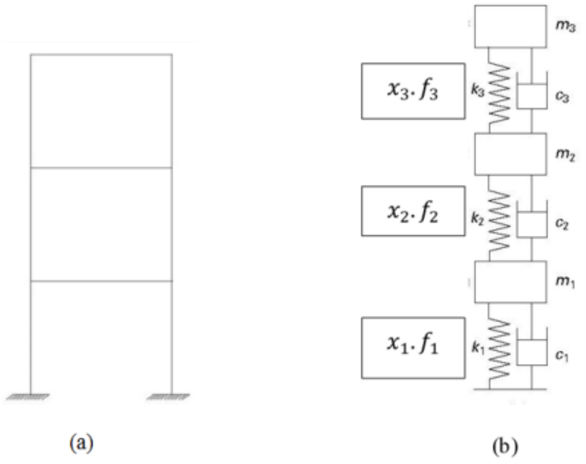


Figure 3.5: Three story building system (a) reinforced concrete building (b) modelled 3 degree of freedom.

Typical approaches to continuous systems, such as the MDOF system, consist on considering the system's shape through a large number of pieces. The notions of compatibility and balance are utilized to find an approximation of the original system, while guaranteeing as much accuracy as possible and taking into consideration a simple solution for each component. This study requires an approximation in order to characterize the behavior of the structure using a restricted number of degrees of freedom.

Another technique for continuous systems is to use a small number of stiff or concentrated masses as contrasted to the system's scattered masses or inertia. Consider the attachment of one mass to another. Using linear or linear coordinates, the motion of the collection of masses is described. These models are classified as discrete mass systems, centralized mass systems, and centralized parameter systems, respectively. Wireless degrees of freedom refer to the smallest set of coordinates essential to identify the deformed shape of the system. An example of a three-story building is shown in Figure 3.5b, which is a three-degree centralized mass model. While analyzing the x-direction dynamics of the multi-story frame, the coordinates X1, X2, and X3 may be considered. Assume that equation (3.2), which depicts the general equations of motion for the three masses of the autogram in matrix form, holds true (Ewins, 2000).

$$[M]\{\ddot{x}(t)\} + [C]\{\dot{x}(t)\} + [K]\{x(t)\} = \{f(t)\} \qquad (3.2)$$

where:

$\{\ddot{x}(t)\}$ is the acceleration vector

$\{\dot{x}(t)\}$ is the velocity vector

$\{x(t)\}$ is the displacement vector

4. Artificial Neural Network Application for Damage Detection

4.1. Introduction

In 1958, Warren McCulloch and Walter Pitts introduced the idea of an artificial neural network. It is characterized as a parallel data processing paradigm for biological neuron models. It's a collection of basic processing units that are densely linked. By weights, every neuron is linked to its neighbors. Continuous training cycles allow for the optimization of weights. Widespread usage of artificial neural networks for processing complicated mathematical models. In several scientific disciplines, including building engineering, neural networks have been implemented. It can learn from experience and examples, and then provide a solution that corresponds to the actual scenario. Numerous sorts of tasks, such as categorization, forecasting, and grouping, are suited for artificial neural networks. Several distinct kinds of artificial neural networks have been devised and utilized for structural damage identification in recent years. There are two primary forms of neural networks: feed-forward and recurrent feedback. These two categories may be subdivided into a number of subtypes, as seen in Figure 4.1.

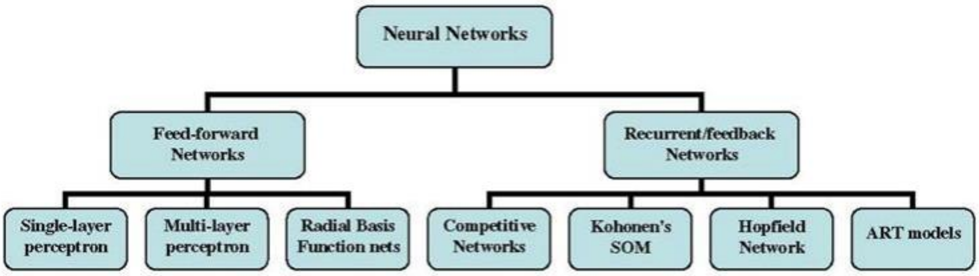


Figure 4.1: Type of neural networks (Jabbari and Talebi, 2001).

In addition to this, multi-layer perceptrons are utilized very frequently. This type of network learning problem aims at minimizing the error function of the free parameters. This approach is beneficial to establish the fitting relationship between the input and target datasets.

4.1.1. Artificial Neuron Model

A crucial element of a deep neural network is an artificial neuron. Its function and design are founded on the notion of biological neurons, which include the nervous system, vertebral column, and peripheral ganglia of the biological neural network. The graphic depicts the similarities between artificial and biological neurons. The nerve cell seen on the left consists of soma, dendrites, and axons, while the artificial neuron depicted on the right has inputs, weights, transfer functions, deviations, and outputs.

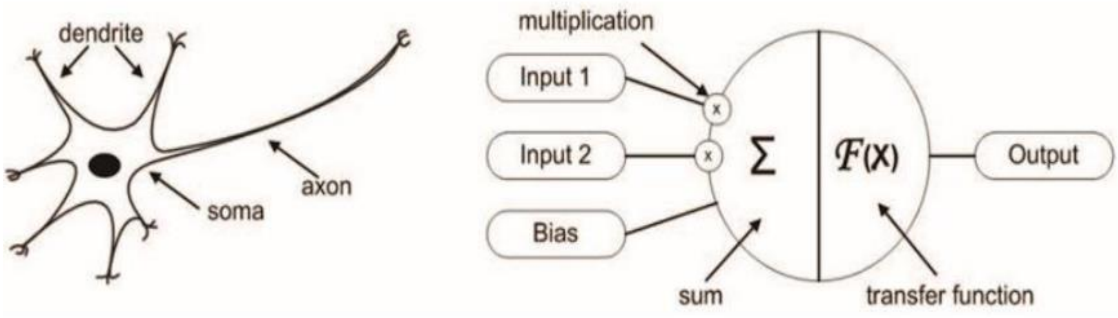


Figure 4.2: Biological and typical artificial neuron (Krenker et al., 2011).

Data from biological neurons that emanate through dendrites is processed by somatic cells and transmitted through axons. For the artificial neuron, the data first enters the neuron via weighted inputs, The artificial neuron then sums the weighted inputs, applies a bias, and processes this total through the transfer function. The artificial neuron then transmits the processed data via the output. Below is the mathematical expression.

$$y(k) = F\left[\sum_{1=0}^{n} w_i(k) \cdot x_i(k) + b\right] \tag{4.1}$$

Where:

$x_i(k)$ is the input value in discrete time k where i rages from 0 to n,

$w_i(k)$ is the height value in discrete time k where i ranges from 0 to n,

b is the bias,

F is a transfer function.

$y(k)$ is the output value in discrete time k.

4.1.2. ANNs Classification

There are generally two types of ANNs. There are two forms of artificial neuron connection networks, based on the number of layers: single-layer networks and multilayer networks. The categorization of the other kind is determined by possible topologies. Individual synthetic neurons are linked based on their architecture. There are two different types of topologies: feed-forward and recurrent.

As could be seen from the Figure 4.3 below, a single layer is the most basic sort of layered network. In a single-layer network, there is no hidden layer since every neuron in the input layer is directly connected to an artificial neuron in the output layer. Consequently, weights connect the neurons of the input layer to those of the output layer.

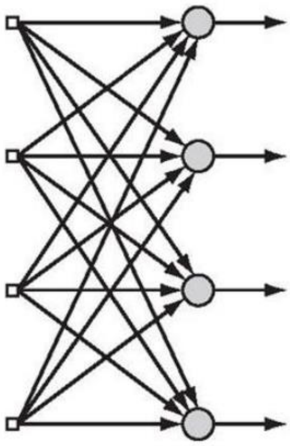


Figure 4.3: Single layer feed – forward network (Hykin, 2009).

The multilayer network is one of the most prominent forms of neural networks utilized by academics; it generally consists of an input layer of units that are fed in progressively as the rest of the network passes through it. After that, neurons in a multilayer hidden layer are connected to the input layer. These neurons perform transfer functions, bias summation, and inputs that are weighted. The output layer's neurons then receive the data. As illustrated in Figure 8.4, the input layer of the rebuilt neural network has ten neurons, the hidden layer has four neurons, and the output layer has two neurons. every time a neuron processes an input result, that result becomes the output result for the next processing cycle, and so on until the final output result is reverted.

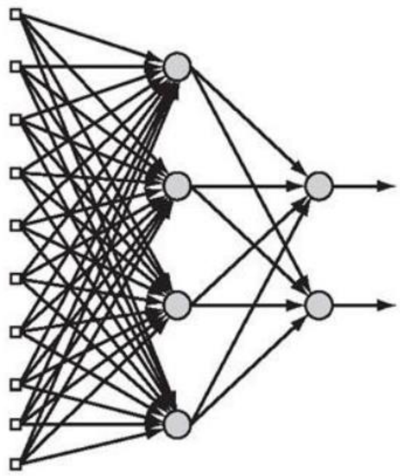
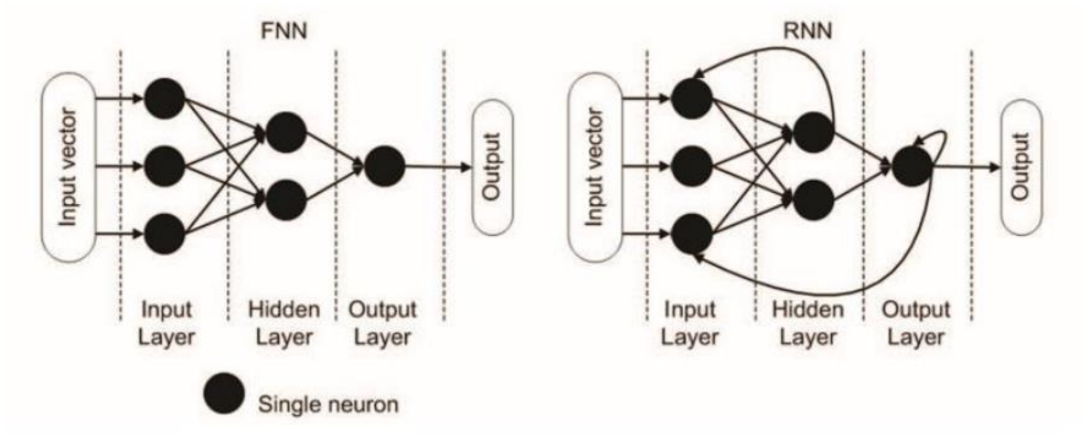


Figure 4.4: Multi-layer feed-forward network (Hykin, 2009).

The Figure 4.5 below illustrates the two remaining basic topologies. The feed-forward architecture is shown on the diagram on the left. In this configuration, the output channel of the neurons is unidirectional, and every layer is connected to the layer below it. On the image on the right, the recursive topology is shown. Data may flow not just at the input but also at the output. It is capable of flowing in both directions, from the output to the input. For these two types of neural networks, the words "feed-forward artificial neural network" and "recurrent artificial neural network" are derived.



Feed-forward FNN Recurrent RNN

Figure 4.5: Feed-forward FNN and recurrent RNN topology of an artificial neural network (Krenker et al., 2011).

4.1.3. Architecture of Artificial Neural Network

An artificial neural network imitates the organic nervous system by using a collection of linked artificial neurons. Through weights, every neuron's action affects the others. The activity of the neural network is governed by how the neurons communicate with one another. The ideal approach to create an artificial neural network that is more efficient is to continuously experiment with it; Nevertheless, this process clearly takes more time, thus it is essential to draw on the knowledge of earlier generations to create an effective neural network rapidly. The architecture of an ANN is composed of five key elements: the number of layers, or the number of neurons per layer; the transfer function.

4.1.3.1. Number of Layers

The multilayer perceptron is one of the most commonly utilized network architectures. An MLP network normally consists of an array of input neurons in one input layer, numerous hidden layers, and an output layer as the final layer of the array, which is also called the last layer. It is worth highlighting that neurons are frequently arranged into groups termed layers to ease processing and mathematical description of the ANN (Krenker et al., 2011). The most optimal number of layers for a neural network typically relies on the amount of noise in the target, the number of training examples, and the complexity of the task, among other factors. It is obvious that neuronal network with more hidden layers can generate problems of overfitting and high variance due to a higher degree of nonlinearity, so to avoid this, two hidden layers are recommended for most cases (Masri et al., 1996), but Hecht-Nilsen (1987) proved that any function can be computed by one by one network with a sufficient number of hidden layers of neurons. Most practical issues employ three-layer (input, hidden and output) or four-layer (input, hidden and output) neural network, nevertheless seldom five-layer or more neural network are utilized.

4.1.3.2. Number of Neurons

Predicting the number of neurons in a neural network layer requires a substantial amount of experience, and although there is no formula for finding the optimal number of neurons per layer, numerous rules of thumb may be utilized to estimate the number of neurons per layer. The geometric pyramid rule is one such rule, which stipulates that the number of neurons should decrease from the input layer to the output layer. Consequently, every layer may contain a variable number of neurons, and every neuron is an independent element that receives a signal from a neuron in the preceding layer, feeds it back as a weighted sum, and then processes it using a transfer function as the input result for the neuron in the next layer.

To determine the optimal number of neurons, the experiment must be conducted on the ANN layer neurons. Overfitting will occur if the number of neurons in the neural network layer is excessive. Underfitting happens when the number of neurons in the neural network layer is insufficient. Overfitting is the deterioration of a neural network's predictive performance cautilized by exceeding the optimal number of network layers or neurons.

4.1.3.3. Transfer Function

The transfer function determines the activity of every neuron. The activation function is a crucial element of the structure of an ANN and must be set artificially. After receiving input from the neuron in the preceding layer, every neuron must sum its input and then replace it into the transfer function. The goal of the transfer function is to prevent the output results from reversing a very broad range, so that the network does not lose its capacity to suppress the training effect. Different types of transfer functions are useful for various circumstances. As seen in Figure 4.6, typical transfer functions include hyperbolic tangent sigmoid, logarithmic sigmoid, linear, saturated linear, and symmetric saturated linear. These transfer functions are also utilized by the vast majority of researchers. Because it is continuously differentiable and nonlinear, sigmoid function is one of the most suitable options for network learning. The output of the hyperbolic tangent sigmoid function ranges between -1 and 1.

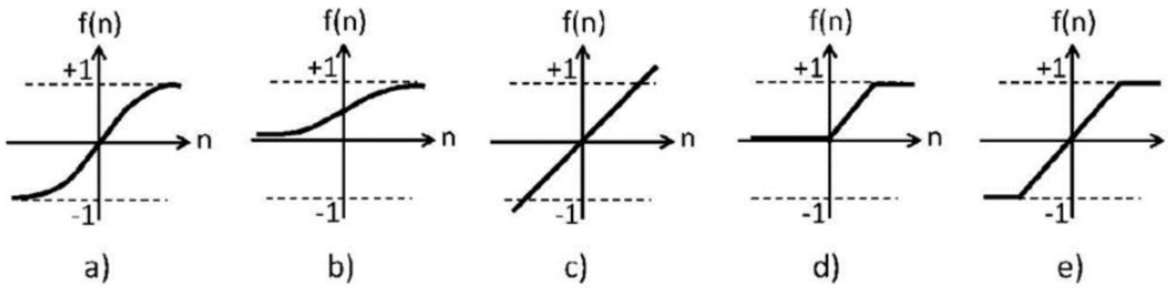


Figure 4.6: a- hyperbolic tangent sigmoid, b- logarithm sigmoid, c- linear, d- saturating linear and e- symmetric saturating linear (Meruane and Mahu, 2004).

4.1.3.4. Weights and Biases

The other two essential ANN elements are weight and bias. Weights are coefficients that quantify the input results between the output results of neurons in the previous layer and the input results of neurons in the subsequent layer. Similar to weight, bias is influenced by a steady input. Despite the fact that ANN networks may be formed without bias or with a bias result of 0, ANN networks with bias are more effective than unbiased neural networks. By modifying both the weight matrix and the bias vector, ANNs may be trained according to a defined method. In other words, bias results only exist in the hidden and output layers and are coupled to the weights that may be modified.

4.1.3.5. Neural Network Learning

There are two primary classifications for neural network types: supervised learning and unsupervised learning. Any specific neural network design is capable of using both learning approaches. The decision of which learning technique to use relies on the data collected during network training. every learning technique corresponds to a number of training methods. Back propagation and learning vector quantization are two of the most commonly utilized techniques that have widespread popularity. The type of instruction utilized in this work is supervised learning. The champion is required to supply a set of training cases, input and output patterns for supervised learning algorithms. A training set (example set) of acceptable network activities is utilized to supply the learning rules.

As the most frequently used neural network model, supervised learning requires the user to provide input and output sets in advance for the neural network to learn. The learning rules are provided by the training set of the network, and when the training is complete, further validation and testing are required.

$$\{x_1, d_1\}, \{x_2, d_2\}, \dots\dots\dots\dots\dots.. \{x_n, d_n\}$$

where:

(x_n) is input to the network,

(d_n) is corresponding target output.

To get the output result closer to the real result, it is necessary to compare the actual output of the network with the goal. The learning rules are then utilized to change the network's weights and bias such that the difference between the output result and the real result is minimized.

Nevertheless, with unsupervised learning, there is no intended output. In other words, unsupervised learning is appropriate when the user is unaware of the desired output of the training function.

Due to its ability to solve nonlinear separable pattern classification problems, the backpropagation learning algorithm is the most widely utilized algorithm in the field of neural networks. Other commonly utilized algorithms include the perceptron learning algorithm, the Hebbian learning algorithm, and the Widrow-Hoff learning algorithm. Multilayer feedforward neural network is most often utilized in backpropagation learning techniques (Fausett, 1994). Depending on the task, the number of neurons in consecutive layers is ordered nonlinearly (Caglar, 2008; Jha, 2007). every neuron has a transfer function that defines how the weighted sum of its input results is translated into its output results, often using a sigmoid or ReLU function.

The method for backward propagation has two crucial parts. The first stage propagates activation from the input layer to the output layer. The second stage is the reverse stage, which propagates the mistakes of the output and input results backward. This stage permits left-to-right modification of the weights and deviation results.

The fundamental premise of backward propagation is to modify the neural network's weights via instance-based learning, and the technique employs a high number of training cycles for repetitive stages. The ultimate objective of the method is to identify the optimal collection of weights so that any input will provide the proper output. In order to obtain the required connection between input and output, the algorithm must continually alter the training network's weights.

In the forward stage, the following equation is utilized to determine the weighted total of the input elements: (Caglar, 2008).

$$\mathrm{net}_j = \sum_{i=1}^{n} w_{ij} \cdot x_i + \mathrm{bias}_j \tag{4.2}$$

where:

net_j is weighted sum of the j^{th} neuron for the received input from the preceding layer with n neurons

w_{ij} the weight between the j^{th} neuron and the i^{th} neuron in the proceeding layer.

x_i is the output of the i^{th} neuron in the proceeding layer.

The input results are then sent through the sigmoid transfer function to compute the output of the j^{th} neuron as follows: (Caglar, 2008). The resulting output (expressed by Equation (4.3)) is guaranteed to be between 0 and 1.

$$out_j = f(net_j)\frac{1}{1+e^{-(net_j)}} \tag{4.3}$$

After training is complete, the output results must be compared to the actual results, and the sum of squared errors and mean errors are computed to determine the neural network's accuracy. Since erroneous data are carried backwards across the network, the weights of every layer undergo minute modifications. Consequently, the backpropagation process must be repeated continually until the desired squared difference error result is obtained, which is often a constant, and the cycle terminates automatically when the error result after a certain number of cycles falls below a predetermined threshold. The SSE is described below..

$$\mathrm{SSE} = \sum_{i=1}^{m} (\mathrm{T}_i - \mathrm{out}_j)^2 \tag{4.4}$$

where:

T_i is target output of the neural network value for i^{th} output

out_j is actual output of the neural network value for i^{th} output

m is number of neurons in the output layer

The mean squared error (MSE) is chosen as the error function and is defined as Equation (4.5).

$$\mathrm{MSE} = \frac{1}{n}\sum_{j=1}^{n}\left(O_t - O_p\right)^2 \tag{4.5}$$

where:

O_t is the target outputs

O_p is the predicted outputs

n is the number of data

MSE indicates the difference between the ANN output value and the desired value

Back propagation method for learning the most utilized algorithm is a multilayer feedforward neural network. Since the backpropagation method develops multilayer feedforward neural networks with the capacity to perform a variety of problems, this algorithm's neural networks are utilized more often than those of other algorithms.

In this research, one of the modal characteristics, natural frequency, is retrieved as an input result to determine the occurrence of damage. In this article, the authors present a neural network-based approach for predicting the degree and location of structural damage. This ANN model uses the natural frequency as an input result, and the damage severity and damage position as output variables. Notably, because the neural network is able to manage the damage process implicitly via the supplied natural frequencies, it does not need a comprehensive physical model of the structure under consideration.

4.2. Artificial Neural Network Model

Numerous artificial neurons, including cells, segments, and units, are carefully interconnected to form a neural network. Neural networks consist of an input layer, one or more hidden layers, and an output layer. The amount of neurons in the input and output layers is influenced by the length of the input and output vectors. The user must identify the number of hidden layers and hidden neurons per layer via experience. every layer of neurons must take the input from the neurons in the layer above or the input values from the layer below. The weights are a key component of linked neurons. The weights are constantly adjusted until the error value falls below a particular threshold or the number of iterations equals a predefined quantity. A bias neuron is an additional, constant-output node in the hidden and output layers of a neural network.

The multilayer perceptron, one of the most prevalent network models, is also known as a supervised network since it requires a desired output value to learn. MLP seeks to design a model that, utilizing historical data, establishes a mapping relationship between input and output. The trained model may then be used to forecast output values when the desired output is unknown. Figure 4.7 is a graphical representation of the MLP network.

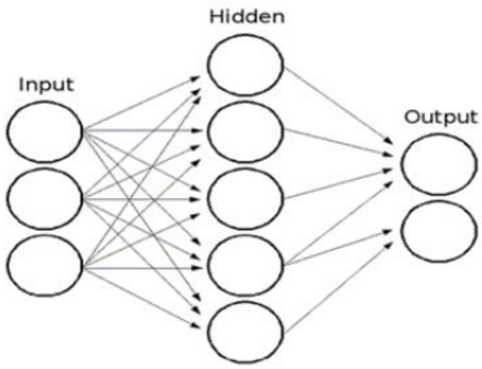


Figure 4.7: Graphical representation of MLP network

The data must be provided to the neural network continuously and repeatedly using the back propagation approach. During every cycle, the output value of the neural network must be compared with the predicted value in order to compute the loss function, which is the difference between the two values. The model is considered "trained" when the difference between the actual value and the predicted value falls below a certain threshold.

4.3. Damage Detection Using ANNs

In engineering, neural networks are being used to predict the extent and location of structural degradation. Neural networks are powerful data processing tools that may be used to modeling, classification, identification, and diagnosis. Artificial neural networks are built on a source equivalent to the network of neurons in the human brain for a variety of reasons. People may utilize neural networks to learn new knowledge first. The strength of neuronal connections and synapses is where information about neural networks is stored. This study used ANN to establish the mapping relationship between injury features (natural frequencies) and injury labels (injury degree and injury location). Before an ANN can be constructed for damage detection, it must be trained on known damage characteristics, along with the relevant damage levels and damage locations. Back Propagation-based Multilayer Perceptron (MLP) is the most often used approach (BP). This method lowers the difference between expected and actual values by solving for the derivatives and continuously adjusting the weights and bias values. In this study, the supervised, multilayer, feedforward neural network with error backpropagation algorithm is the most used ANN model.

4.3.1. I-beam Simulations and Data Preparation

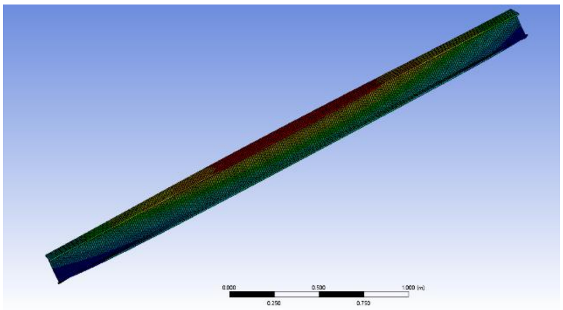
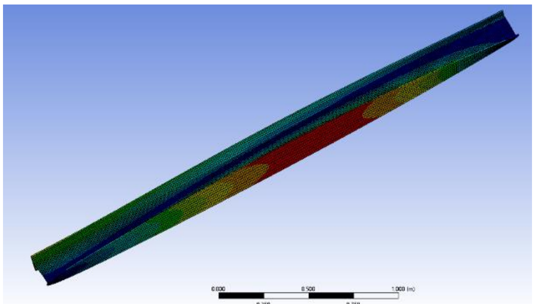
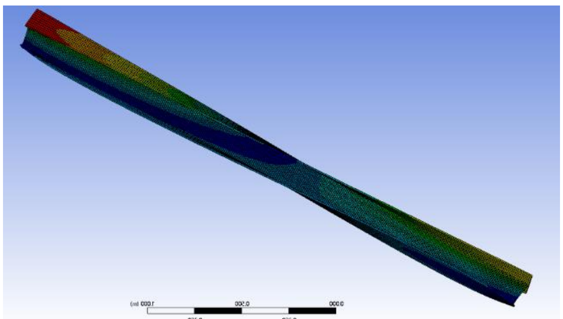
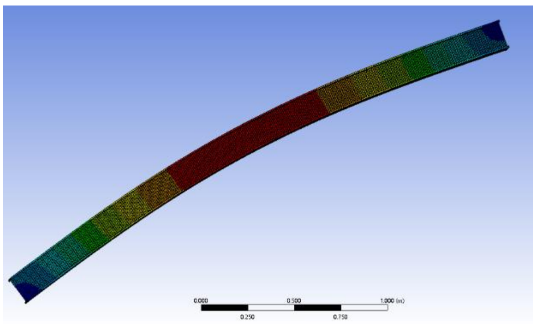
The modeling of a steel structure begins with the construction of a geometric model. Initially, a geometric model is constructed using the ANSYS finite element software. The structure's frequency is altered when a fault is introduced. Using the natural frequency, the extent of the defect's damage may be measured. In this experiment, an artificial neural network (ANN) was used to identify the I-damage beam's degree and damage location, and ANSYS was used to extract the beam's natural frequency. Its width was 152.89 British pounds and its length was 3 meters. After the natural frequencies were extracted, the structural damage quantity and location were used as the ANN's input and output values, respectively. To calculate the first five natural frequencies of the structural domain, an I-beam geometry model is developed. Due to the model's use of a simply supported beam, fixed boundary conditions are applied to one end, free boundary conditions are applied to the other end's z-direction, and fixed boundary conditions are applied to the x- and y-axes.

Input parameters of the neural network are the first five natural frequencies, and output parameters are the amount and location of structural damage. A large number of inputs and outputs are required as data sets for the proper operation of an artificial neural network. Due of the long, labor-intensive, and expensive method, it is not possible to gather accurate trial data.

A finite element technique may be applied to simulate the position and amount of damage, as well as to generate realistic frequency values, in order to simulate the damage location and quantity.

The following I-beam parameters, including geometry, physical properties, etc., are constant throughout The technique. The steel has a density of 7850 kg/m3, a Poisson ratio of 0.2, and an elasticity modulus of 2×10^{11} Pa. The length is 3000mm in total. the beams' dimensions The beams have 88.7 mm flange widths, 152.4 mm section depths, 7.7 mm flange and 4.5 mm web thicknesses, respectively. To represent the intensity of the I beam's damage, the model contains a 3mm-by-75mm slot that is progressively widened by 3mm. Define the damage's position at (2/15), (4/15), and (6/15)L. A total of 4×25(=100) simulations with a mesh size of $0.01m^2$ were executed.

A total of one hundred datasets were generated for the inquiry. The 500 natural frequencies used to train the network were comprised of the first five natural frequencies from every dataset. ANSYS analysis of a 3D finite element model with a single damage was used to determine the first five natural frequencies of the modality. Although neural networks have been used to tackle a variety of civil and structural engineering problems, they have not yet been applied to I-beams with varied degrees of failure severity.

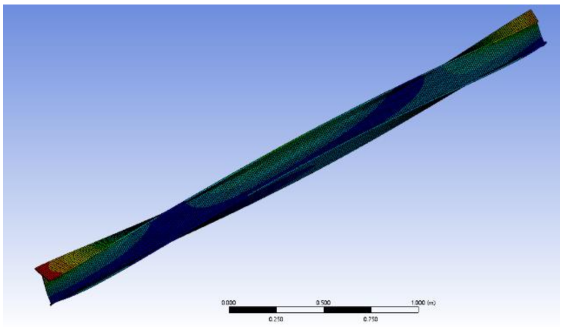


Figure 4.8: First five mode of undamaged I beam

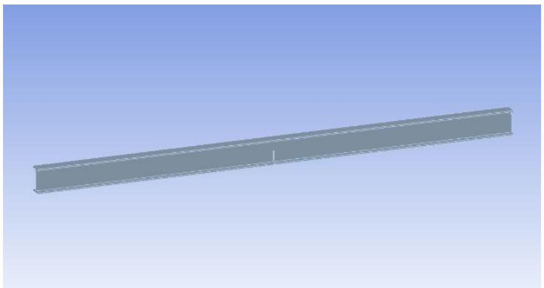


Figure 4.9: A 75mm cut slot of damaged I beam at location (1/2)L

Table 4.1: Ratio of damage depth to height of beam for different cut slot

Cut slot(mm)	d/h	Cut slot(mm)	d/h
3	0.02	42	0.28
6	0.04	45	0.30
9	0.06	48	0.31
12	0.08	51	0.33
15	0.10	54	0.35
18	0.12	57	0.37
21	0.14	60	0.39
24	0.16	63	0.41
27	0.18	66	0.43
30	0.20	69	0.45
33	0.22	72	0.47
36	0.24	75	0.49
39	0.26	-	-

Table 4.2: . Ratio of damage location from support to length of beam

Damage location(l)	l/L
(2/15)L	0.133
(4/15)L	0.267
(6/15)L	0.400
(1/2)L	0.500

4.3.2. MATLAB Code Demonstration

Using a feedforward multilayer neural network, this investigation identifies the relationship between natural frequencies and the amount and location of structural degeneration (MLP). As illustrated in Figure 8.9, natural frequencies were selected as input values, while the degree and location of structural damage were selected as output values. MATLAB was used effectively to develop the code for a multilayer perceptron as part of the ANN model creation process.

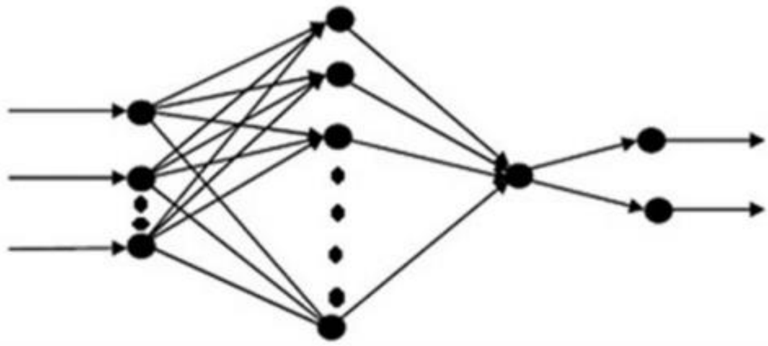


Figure 4.10: Schematic representation of the proposed ANN.

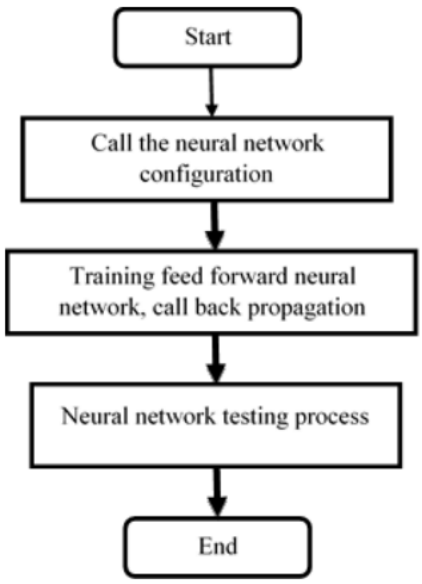


Figure 4.11: General flow chart for the ANN Code.

The two most used backpropagation algorithms are Levenberg-Marquardt and conjugate gradient. every algorithm is quite efficient. Hagan and Menhaj compared these two training approaches in 1994. It was revealed that Levenberg-Marquardt outperformed the Conjugate gradient approach in terms of rapid convergence speed during both training and testing. In this study, the backpropagation network was thus trained using the Levenberg-Marquardt algorithm. This strategy is based on a function that minimizes the sum of squares of other nonlinear functions. Bishop (1995) and Hagan et al. (1995) devised the algorithm as a variant of Newton's approach. When the mean squared error (MSE) is infinitesimally near to zero, it is considered that the artificial neural network has been trained.

As the first step of ANN learning, the dataset is separated into the training set, validation set, and test set. Using the training data, a network model is formed, and weights and bias values are continuously changed to decrease error. When the degree of generalization of the network ceases to change, training is terminated and the degree of generalization is assessed using the validation set. Using the test set, the training results of the neural network are assessed. It can independently assess the neural network's performance. The data set is divided into training, validation, and test sets according to a preset proportion. As output variables, the extent and location of structural damage are reported, while natural frequencies are included as input variables. The training set, validation set, and test set every serve a separate function. The training set is used to fine-tune the weights and bias values to suit the goal function, the validation set is used to minimize overfitting, and the test set is used to independently check the accuracy of the neural network to determine whether its predictive power meets the target criteria. Training set, validation set, and test set are used for learning, parameter modification, and network performance assessment, respectively.

Transfer function is a fundamental component of the ANN model. Various transfer functions have differing effects on the ANN. Figure 4.12 depicts the hyperbolic tangent sigmoid function and pure linear neuron, both of which are common functions.

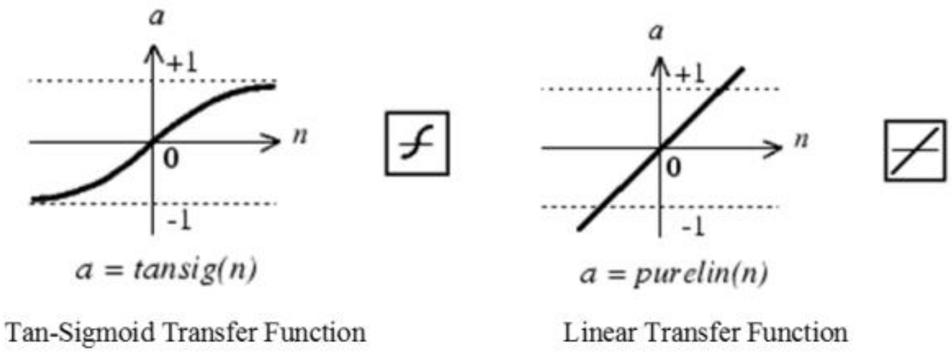


Figure 4.12: Types of transfer function.

These transfer functions take the input and squashes the output into the range of -1 to 1, according to the expression defined in Table 4.3 : where a is the output and n is the input.

Table 4.3: Transfer Functions in hidden and output layer (Hykin, 2009).

Name	Input/Output Relation	Icon	MATLAB Function
Hyperbolic Tangent Sigmoid	$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$		Tansig
Linear	$a = n$		Purelin

4.3.3. Proposed ANN Based

Using the finite element analysis of a simply supported beam with dimensions of 152.89 UKB and a length of 3 m to generate multiple input-output data, a system for damage detection was devised. Before acquiring the actual input-output data, ANSYS did a modal analysis based on the magnitude and location of the damage. The damage level was calculated as the ratio of damage depth to beam height, and a total of 25 various damage depths were established in this experiment, ranging from 3 mm to 75 mm with a continuous 3 mm increase between every damage depth. Four damage sites were created at (2/15), (4/15), (6/15), and (1/2)L, respectively.

Back-propagation neural network with three layers (input, hidden, output) was trained to recognize the natural frequencies of a simply supported beam with 25 different degrees of damage at four separate locations. The feedforward backpropagation approach outlined in Table 4.1 was used to train the artificial neural network.

Since there is no recognized criteria for finding the optimal number of neurons, two distinct experimental methods were used to estimate the number of neurons in the input layer or the number of natural frequencies in this study. Due to the fact that the differences between the first three natural frequencies in the first experiment were so small, the results were erroneous and did not correctly reflect the varied degrees of structural damage. In the second experiment, there were five natural frequencies rather than four, and as a result, the results were more accurate and the margin of error was less than in the first experiment. The first five natural frequencies were chosen as input values for neurons because this implies that adding five additional neurons to the input layer generates more accurate results and can more accurately predict the level and location of structural damage. On the other hand, it is not recommended to use higher modal natural frequencies as input values, since having too many neurons in the input layer may result in unstable ANN performance.

The back propagation algorithm used in this inquiry is Levenberg-Marquardt. In a neural network, information flows from the input layer through the hidden layer to the output layer. This means that the neural network has no loops or circuits. Figure 4.13 displays the model constructed for this study, a three-layered MLP neural network (input layer, hidden layer, and output layer). Five neurons comprise the input layer, which produces two distinct types of information: the level of structural damage and its location. The neurons in the output layer are transmitted using a linear transfer function with a sigmoid transfer function.

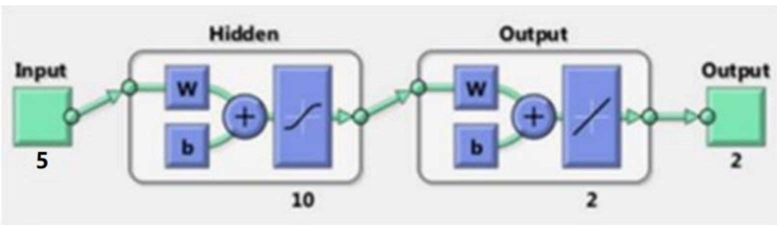


Figure 45.13: The proposed classification neural network for damage detection.

This neural network's input and output sets are randomly divided into three groups, with 80% of the input and output sets going to the training set, 10% to the validation set, and 10% to the test set, which is used for independent network testing.

Overfitting, one of the most prominent instances of neural networks, often occurs when the error in the training set converges to zero. This is a result of the network's comprehensive understanding of the training examples, but its inability to reliably predict future occurrences. As a new condition arises, the disparity between predicted and actual values grows.

4.3.3.1. Input-output data

For the first five natural frequencies, 25 unique damage levels and a total of four structural damage locations have already been identified. Table 4.4 lists the first five natural frequencies at (1/2)L. As noticed in the table, when the degree of structural damage was varied, significant variations in the natural frequencies occurred. Consequently, the output of the neural network was the level of structural damage.

Table 4.4: First five natural frequency of damaged I beam at location (1/2)L

Cut slot(mm)	Mode 1(Hz)	Mode 2(Hz)	Mode 3(Hz)	Mode 4(Hz)	Mode 4(Hz)
3	20.293	36.399	48.411	56.086	81.681
6	20.238	36.147	48.381	55.698	81.683
9	18.321	30.803	47.734	53.056	81.554
12	18.308	30.782	47.716	52.554	81.532
15	18.298	30.771	47.7	52.062	81.508
18	18.279	30.742	47.674	51.52	81.452
21	18.266	30.723	47.659	51.001	81.401
24	18.258	30.71	47.646	50.505	81.353
27	18.251	30.702	47.639	49.975	81.31
30	18.236	30.68	47.622	49.392	81.194
33	18.223	30.664	47.61	48.814	81.062
36	18.215	30.653	47.603	48.266	80.942
39	18.199	30.633	47.566	47.662	80.716
42	18.188	30.617	46.991	47.589	80.465
45	18.186	30.615	46.365	47.586	80.368
48	18.164	30.587	45.637	47.572	79.666
51	18.149	30.568	44.929	47.563	79.038
54	18.145	30.564	44.23	47.563	78.65
57	18.127	30.542	43.423	47.557	77.548
60	18.115	30.525	42.622	47.548	76.374
63	18.104	30.512	41.792	47.545	75.503
66	18.097	30.503	40.987	47.543	74.758
69	18.072	30.47	40.011	47.534	72.583
72	18.054	30.447	39.053	47.529	70.948
75	18.046	30.436	38.219	47.525	70.219

In this feedforward artificial neural network (FFANN) classifier, the natural frequencies serve as the input set, while the structural damage location and severity serve as the output values. 80 percent of the 100 data sets were randomly selected for training as the training set, 10 percent were used to check the network's degree of generalization as the validation set, and the remaining 10 percent were utilized for independent network testing as the test set.

4.3.3.2. Early stopping network

As indicated in Table 4.5, there are a number of MATLAB-specified criteria that may be used to halt the neural network training early. During the training method, the window's progress is regularly updated. When the mean square error (MSE) for training samples falls below a specified threshold, when there is no error improvement for a given period of cycles, or when the training process has reveryed its maximum number of iterations, the training process is concluded. In addition, the number of validation checks determines the number of following iterations during which the validation performance must deteriorate before the training concludes (Beale et al., 2012).

Table 4.5: The criteria of early stopping training

Parameter	Stop criteria
Min. grad.	Minimum gradient magnitude
goal	Minimum performance value
epochs	Maximum number of training epochs (iterations)
Max. fail	Maximum number of validation increases
time	Maximum training time

In addition to the conditions for early termination of the training network, the training process may be terminated by pressing the stop training button in the training window, as seen in Figure 4.14. This is conceivable if the performance function does not degrade considerably after several iterations or extensive training. The train command may afterwards be used to retrain the network. As a result, after the previous cycle concludes, the network will continue to be trained.

When generalization ceases to improve, as shown by an increase in the mean square error (MSE) of the validation samples, the training network in this study automatically shuts down.

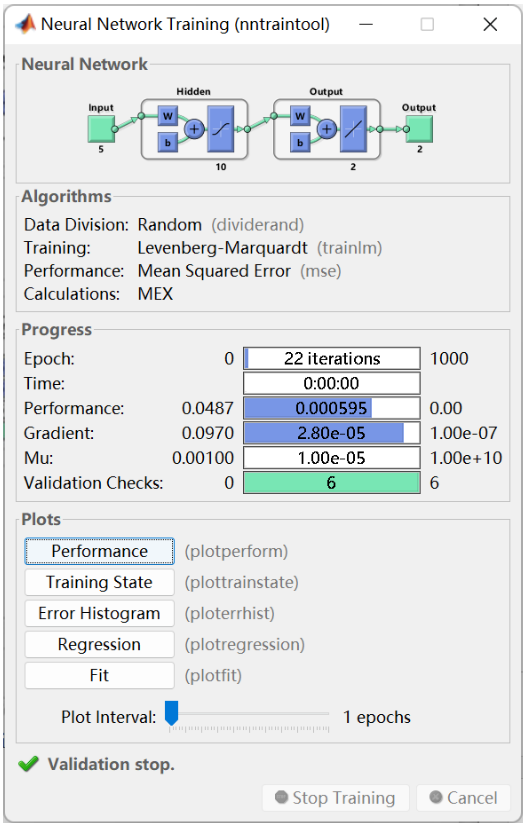


Figure 4.14: MLP network training window.

4.3.3.3. Performance of the network

Figure 4.15 depicts the efficacy of feed-forward back propagation (FFBP). The graph illustrates how the network's performance increased during the training process. Mean square error (MSE) is used to measure the performance of a network and is shown in log format. Clearly, after training the neural network, the MSE has decreased dramatically over time. The results demonstrate that the study's hypotheses were plausible. Around 16 epochs, the mean-square error is at its lowest point. Around epoch 16, the test set error (training, testing, and validation error) of the network stabilizes, the MSE value is 8.3122×10^{-4}.

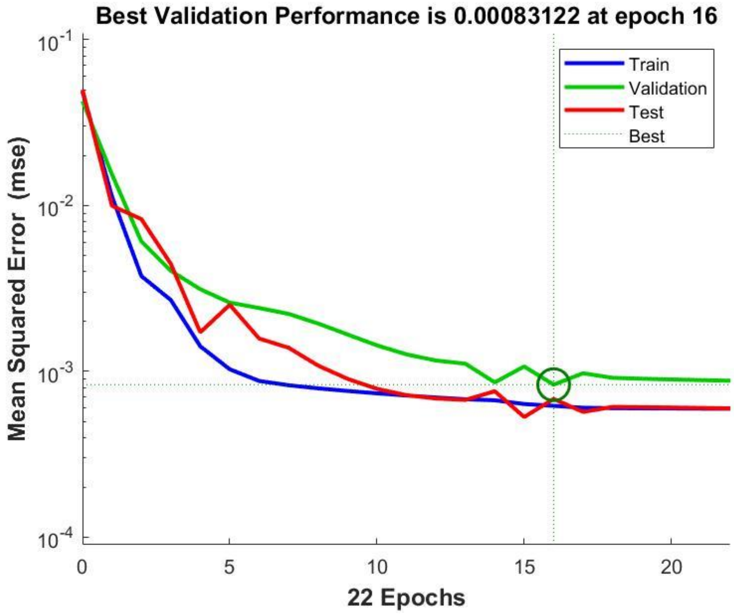


Figure 4.15: Validation Performance (MSE) of FFBP.

At epoch 16, the last MSE, the network in this study had a negligible amount of test set error, making it easy to detect and assess the network's performance. Likewise, the features of the regression set are same. After training, the neural network's ability for regression analysis may be assessd. Figure 4.16 depicts the regression graphs for the training, validation, and test sets of output of the networks in relation to the goals. The validation and test results for the same number indicate that the average values are likewise more than 0.97. According to training, testing, and validation data for plot fitness, the correlation between the objective and output is quite strong. Notably, the suggested neural networks were able to establish the relationship between natural frequencies and the associated empty state. As a result, it was discovered that the network knew how to reduce the overall estimate error.

The data must lie on a 45° line where output of the networks and targets are equal for the graph to be faultless. every of the data sets included in this experiment had a regression value R of 0.97 or more and had very strong match correlations. If more precise neural output of the networks are necessary for the intended purpose, the re-train button may be used to retrain the network. Retraining the network will alter the original weights and biases, which might result in enhanced network performance. When the majority of errors are near to zero, a better-trained network model has often been created.

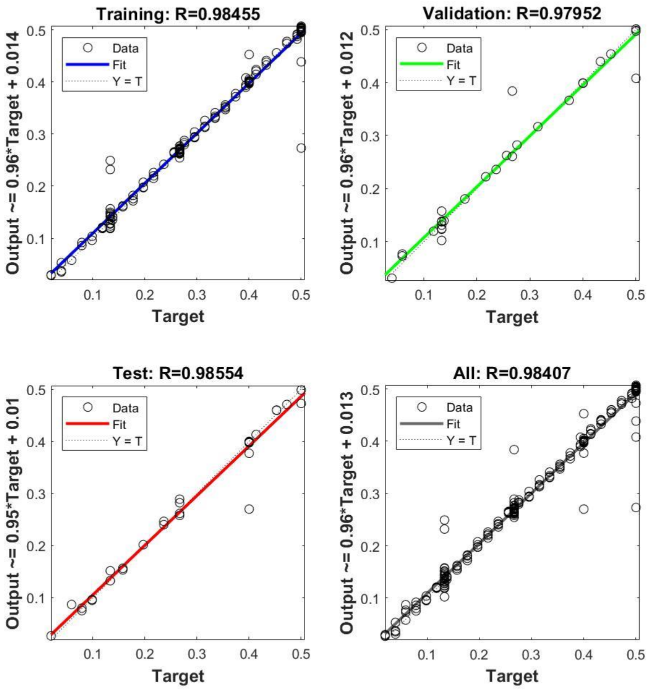


Figure 4.16: The Regression values between the actual and target values (FFBP).

The regression of test data is a critical statistic for analyzing the performance of neural networks. The neural network is intended to respond and adapt to environmental changes in a timely manner, and the technique requires the user to set confidence intervals for assessing the reliability of output of the network.

4.4. Result Analysis and Discussion

This project's objective is to train ANN models for structural damage identification utilizing natural frequencies, structural damage locations, and structural damage levels. Fresh data was utilized to test the trained ANN model's predictions using the most recent information.

Table 4.6 shows the fraction of discrepancy between actual and predicted damage levels and damage locations. Regarding identifying the severity and location of structural damage, these results will be considered the output of the proposed ANN classifier. The table demonstrates that the projected extent and location of structural damage by the ANN model do not precisely correspond to the actual extent and location of structural damage. Despite the fact that the ANN model cannot accurately predict the amount and location of structural damage based on the first five natural frequencies, a comparison of the results demonstrates that it can offer a reasonable approximation, demonstrating that it is suitable for this study.

Table 4.6: Comparison of actual and prediction damage detection (severity and location).

Case	Actual value		ANN Prediction value		Error % Severity	Error % Location
	Severity	Location	Severity	Location		
1	0.433	0.133	0.427	0.118	1.3	1.1
2	0.236	0.133	0.220	0.138	7	3.6
3	0.079	0.133	0.117	0.150	48.1	12.3
4	0.276	0.267	0.284	0.254	3.1	4.9
5	0.157	0.267	0.164	0.270	3.9	1.3
6	0.039	0.267	0.033	0.300	15.7	12.4
7	0.335	0.400	0.339	0.399	1.4	0.3
8	0.276	0.400	0.286	0.394	3.6	1.5
9	0.177	0.400	0.161	0.416	9	4
10	0.492	0.500	0.503	0.506	2.1	1.2
11	0.315	0.500	0.304	0.497	3.6	0.7
12	0.118	0.500	0.113	0.508	4.4	1.6

4.5. Summary

This chapter is devoted to artificial neural networks. It contains information about artificial neural networks. At the beginning of the first part, models of neural networks are discussed. Following is an introduction to neural network models and an explanation of neural network topologies.

It also gives context for artificial neural networks (ANN) based on damage detection techniques. This chapter introduces a non-model-based technique for determining I-beam damage locations and severity. This study introduces four structural damage locations and twenty-five varied degrees of structural damage to train the capabilities of an artificial neural network. The FFBPNN was trained using the first five natural frequencies, and the completed ANN model was utilized to predict the severity and location of structural degradation.

The regression analysis of the test data indicates that the proposed ANN model can predict both the magnitude and location of structural degradation. The test set is utilized to assess the ANN model, and the results indicate that it has strong predictive capability even for unobserved data.

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