Estimating Bridge Deterioration Age Using Artificial Neural Networks

استخدام الشبكة العصبية الاصطناعية لتقدير تدهور الجسور

by

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Abstract

Deterioration of reinforced concrete bridges is major issue in structural engineering due to the difficulty of estimating or predicting the service life of the bridge. Two types of models were developed to estimate the service life, the deterministic and probabilistic models. Nevertheless, the reliability of these models is questioned since they do not account for the many factors involved. Therefore, for this research artificial neural network is used to estimate the deterioration age for RC bridges based on deterioration data. Historical records of bridges located in London is used to train and test ANN. Feedforward neural network is designed to be able to estimate the deterioration age. ANN inputs are bridge type, member type, exposure, and defects while the target is the defects age. Since there are no standard neural network deterioration models, Design of experiment is conducted to select and monitor the most important parameters that would affect ANN performance. Learning algorithm, Number of hidden layers, number of hidden neurons and Transfer function are the four parameters selected for factorial design. Each factor has low and high-level options making 16 different combinations of neural networks. ANN analysis is run on MATLAB and Mean Square Error (MSE), regression and error histogram results are used to evaluate the performance of ANN. The results were mediocre reflecting the type of data provided in neural network training. ANN models could successfully train more than half of the data to achieve the target, However, the rest of the data were not able to achieve the desired output. Furthermore, Analysis of Variance (ANOVA) is used on MSE to determine which parameter influenced the outcome. Hidden neurons are significant factor were MSE of 10 neurons is smaller than MSE of 20 neurons, indicating a better performance for ten neurons models. Then, the deterioration scenarios are compared with ANN output age. Footbridge bridge and compression members had the longest average for service life.

الملخص

تدهور الجسور من الخرسانة المسلحة مشكلة كبيرة في الهندسة الانشائية بسبب صعوبة تقدير أو توقع مدة الخدمة لهذه الجسور. لذلك طور نموذجين لتقدير مدة الخدمة، و هما النموذج الحتمي و النموذج الاحتمالي. ولكن لايستطيع الاعتماد كليا على النموذجين بسبب عدم احتساب الكثير من العوامل المؤثرة في تدهور الجسور. ولذلك تم استخدام الشبكة العصبية الاصطناعية لتقدير تدهور الجسور . وتم استخدام سجلات مؤرخة عن جسور في لندن لتدريب و اختبار الشبكة الاصطناعية. صممت الشبكة العصبية الامامية لتقدير عمر التدهور. و معطيات الشبكة العصبية هي نوع الجسرو نوع العنصر و التعرض البيئي و الضرر بينما الهدف هو عمر الجسر . و بسبب عدم وجود تصميم محدد لنموذج الشبكة الاصطناعية لتدهور الجسور، تم اتباع خطوات تصميم التجربة لتحديد و مراقبة العوامل المؤثرة في الشبكة. خوارزمية التعلم و عدد الطبقات الخفية و عدد الاعصاب الخفية و دالة التحول هي العوامل الاربعة التي اختيرت لتصميم الاختباري . لكل عامل يوجد المحتوى السفلي و العالي مما يولد 16 احتمال للشبكة العصبية الاصطناعية .تم استخدام مات لاب(MatLab) لتحليل هذه مجموعات . و لقياس مدى دقة الشبكة العصبية تم استخدام معدل الخطأ المعياري المربع و خط الانحسار و الرسم البياني .كانت النتائج مقبولة وتعكس نوعية البيانات المعطى للشبكة الاصطناعية . نجحت الشبكة العصبية في تدريب نصف البيانات المعطى لتحقيق الهدف ولكن النصف الاخر لم يستطع اعطاء النتائج المرجوة. بالاضافة تم اجراء تحليل التباين (ANOVA) على معدل الخطأ المعياري المربع لتحديد أي من العوامل كان مؤثرا على النتائج . الاعصاب الخفية هي عامل مؤثر على النتائج حيث كان معدل الخطأ لعشرة من الاعصاب الخفية أقل من معدل الخطأ لعشرون من الاعصاب الخفية ، مما يعني أداء أفضل لعشرة من أعصاب الخفية . و تم مقارنة سيناريوهات التدهور باستخدام العمر الناتج من الشبكة الاصطناعية . حيث أن جسور المشاة و أعضاء حمل الضغط أظهرت أطول معدلات لمدة الخدمة

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DEDICATION

I dedicate this dissertation to my family and friends who never stopped supporting and encouraging me to finish the research. I also dedicated to myself for being able to complete the dissertation, despite being a part time student with tiresome full-time job. Lastly, I dedicated this research to my fellow students at BUiD

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LIST OF ACRONYMS/ABBREVIATIONS

ESL: Estimated Service Life

RSL: Referenced Service Life

P: Probability Matrix

A.I: Artificial Intelligence

ANN: Artificial Neural Networks

FFNN : Feedforward Neural Networks

Y: Neuron Output

f: Transfer Function

w: Weights of the input

X: Input

b: Bias

n: Neurons

X_{t+1} : vector of weight and bias

α_{k} : Learning Rate

g_{k} : gradient

$O\ :\ outputs$

$T\ :\ Targets$

dof: Degree of Freedom

SS: Sum of Squares

FT: Footbridge

OV: Overbridge

MSE: Mean Square Error

ANOVA: analysis of Variance

Chapter 1: Introduction

1.1 Background

The infrastructure facilities for transportation such as bridges and tunnels are vital for urban development and stabilization. Bridges are the most important infrastructure facility for city or country. The term bridge comes from connecting things or points together. The importance of highway bridges could reach to national level, because they are the backbone for transportation and movement. Designing and constructing bridges can be challenging but structural engineering has overcome all the obstacles to deliver the world's most iconic bridges such as; Millau Viaduct bridge in France, Skyway bridge in Florida and Magdeburg Water bridge in Germany. Establishing international codes like ACI and BS has made the designing procedure easier. Also, combining theoretical with empirical information in these codes has empowered the structural design. Furthermore, the factor of safety applied to the design process has increased the life expectancy of bridges. Most of the constructed bridges are designed for service life of 100 years and beyond. Bridges are subjected to different type of loads; dead load, live Load, wind load, seismic loads and etc. The live load is major concern when designing a bridge and they cause abrasion and fatigue. That's why bridges are subjected to unexpected degradation. Since bridges are highway and transportation structures, the environmental exposure could lead to a faster deterioration rate. The deterioration process of bridges is stochastic Therefore, scheduled inspections for constructed bridges are necessary to obtain the occurred degradation. Bridge Management system (BMS) is established in many countries to keep historical records of bridges status and the life cycle. Bridges construction materials are usually concrete, steel and wood. Concrete is very durable material and when steel is embedded inside it to address the tension forces, reinforced concrete becomes the most durable and used construction material. Nevertheless; bridge inspection records imply that RC deteriorates faster than expected which means that concrete durability can be compromised. This issue is becoming critical in many developed countries such as USA and UK. Degradation of highway bridges cost time and money.

To tackle the issue of degradation, a deterioration model is needed to estimate the service life or degradation age. Several methods developed to predict the stochastic degradation process of RC bridges. Three main techniques are used for developing the deterioration model. Deterministic and Probabilistic approaches are the most two common type of methods to develop a service life model. These techniques are used frequently, However, they fall short in providing reliable results. Recently, scholars are interested in exploring Artificial Neural Network capability in estimating the deterioration process of bridges

In the age of computers and technology, Artificial Intelligence approach is the trend for many engineering fields, where complexity and variability exists. This research will focus on using Artificial Neural Network to estimate the deterioration age for bridges using historical records.

1.2 Research Objectives

The research question for this study is to explore Artificial neural network efficiency in estimating the deterioration age for RC bridges. Since limited studies are available for neural network usage in RC deterioration modelling, design of experiment is utilized in this research to investigate the parameters effects on ANN performance. Instead of exploring one factor at a time effect on NN, a controlled experiment is conducted to measure the results. The followings are the objectives of this Dissertation: -

- Determine if the chosen neural network type is adequate for deterioration modelling
- Establish the ANN design parameters that may impact the performance of network
- Perform Design of experiments to determine which parameters affects ANN
- Compare the historical deterioration age with ANN estimated deterioration age
- Understand the importance of accurate database for deterioration modelling

1.3 Research Significance

In this research, experiment is performed to examine how the designed Artificial Neural Network behaves in terms of estimating the response factor which is the defects age. The important design parameters are chosen and their influence on the results are checked and recorded. This could provide insight on how to design ANN model for deterioration estimation, as a result it might be used as reference for upcoming work on the subject by minimizing the trial and error process. Furthermore, this research provides a general perspective on the three deterioration methods which could assist in selecting the suitable method for coming studies. Moreover, the analysis of large historical database to be used for training ANN, can be a major guideline on how to handle database and use them in processing neural network. In general, this research is unique by combining two different fields, the structural engineering field and computer science field, to solve a critical problem like RC bridge deterioration and could be used as a reference point for many studies to come

1.4 Research Challenges

The use of artificial neural network in civil engineering is limited and underdeveloped. This study aims to provide an example of using one of Artificial Intelligence techniques, ANN in solving one of the challenges facing civil engineers which is the RC bridge deterioration modelling. Unlike design process, deterioration is complicated and has many variables to predict. The designing process of ANN is a challenge in itself due to the lack of examples in exploring the different combination in ANN. Furthermore, deciding the type and diagram of artificial neural network suitable for this research took a lot of research digging and some trial and errors. Also, trying to model neural network in justified way led to a research on the best method to do so and design of experiment was found to be the appropriate technique. Moreover, using design of experiment required a systematic approach to the problem which resulted in a lot of models to be designed and analysed. In addition, the analysis of the database was demanding due to the following reasons: -

- Large and scattered database
- Summing up the crucial factors from other irrelevant factors

- Missing and inaccurate information

Since the database is unique and raw, the process and analysis is described in chapter 4. The way ANN results are presented might not be clear enough for civil engineering scholars, so the estimated deterioration age is presented via degradation scenarios through graphs and tables to present insight on neural network outcomes.

1.5 Dissertation Outline

Chapter 2: Provides a review of deterioration causes for reinforced concrete and degradation models. The two approaches, deterministic and probabilistic are discussed showing the advantages and disadvantages of both methods.

Chapter 3: Artificial Neural network are explored in detail with providing its technique, types, and the recent research on its applications for bridge service life.

Chapter 4: Process and Analysis of the bridge database constructed in London, UK to obtain the most useful information to serve as input for neural networks

Chapter 5: Explores the research question and design process for artificial neural network to estimate the deterioration age of RC bridge. Also design of experiment is discussed in detail.

Chapter 6: Shows the results of artificial neural network and the statistical analysis for design of experiment . Also, the deterioration scenarios are presented with estimated defects age

Chapter 7: The last section in this study, provides a closure to the research objective, methods, and end results. Also, a correlation between this study and future work

Chapter 2: Literature Review on Concrete Deterioration and Degradation Models

In this section, the deterioration causes of reinforced concrete bridges are discussed. Also, the two most used deterioration modelling methods are reviewed along with their advantages and disadvantages.

2.1 Reinforced Concrete Bridges

Reinforced concrete is composite material with high durability and strength, thus very proper for constructing bridges. There are many structural types of concrete bridges such as slab bridge, Box Bridge, Arch Bridge, cable stayed bridge, segmental bridge, and I Girder bridge (Concrete Bridge Types 2017). There are 400,000 conventional RC bridges and prestressed concrete in United States. Two third of constructed bridges in USA are made by reinforced concrete ("Highways and Bridges" 2017). More than 100,000 bridges in UK where concrete is used as the main or supporting material. The construction of concrete bridges in Europe began in 1850 and by 1930, there were 2000 concrete bridges in UK. The usage of RC bridges determines the design and construction technique. Four main types of bridges based on the usage, e.g. Foot bridge, Rail Bridge, Road Bridge, and River Bridge (CBDG 2017). Footbridge is designed to serve pedestrians and their light weight load bearing requirement made these bridges free for engineering innovation compared with other bridges. Rail Bridge and Road bridge serve trains and vehicles and could be viewed as overbridge if the traffic passes over road or railway

2.2 Deterioration of RC Bridges

Reinforced concrete bridges are the most well-known type of bridges. The combination of concrete and steel make up for the tensile weakness in concrete. In addition, Durability is one of the advantages of concrete, nevertheless, there is uncertainty revolving around the concept of concrete durability. According to (Gode k & P.A 2009) one of the major problems facing RC bridges is the early deterioration of the structures, where the durability of concrete fell short of the expected service life of the bridges. The durability term is vague to quantify and measure, so the best method to define durability is the ability of concrete to withstand and resist the deterioration process and to maintain the required physical characteristics and mechanical properties in adequate condition through the expected service life. Some factors can reduce the resistance of concrete to deteriorate such as default structural design, chemical attacks, natural disasters, abrasion, fatigue, construction and maintenance, overloading, steel corrosion and other exposures and defects that could cause durability to decrease.

2.3 Causes of Deterioration

Concrete has high compressive strength and the occurrence of deterioration is not common happening. According to Basheer, Chidiact and Long (1996) the 400 studies performed on the concrete deterioration in the last two decades showed some of the causes of deterioration were recorded to have the highest cause of the degradation like steel corrosion and carbonation. The coming section will discuss the degradation causes and types in details.

2.3.1 Physical Process

- **Freeze and thawing Cycles**

  This process happens when moisture or water inside the concrete pores freeze to ice and expand. The moist could be already inside concrete or it leaked inside from surface cracks. When the temperate drops and water freezes which causes expansion in the size, this will apply internal tensile pressure on the pores. Repeated cycles of expansion and shrieking would cause the concrete to crack and burst (Mehta & Monteiro 2006). Many studies from the previous century has discussed this process in details (Powers, 1945; Powers, 1949; Powers and Helmuth, 1953; Beaudoin and MacInnis, 1974; Jacobsen et al., 1996; Cai and Liu, 1998; Coussy, 2005). This is a major problem for concrete bridges in cold countries where de-icing salts are used which further increases the problem. According to Amleh & Mirza (2004) states that the extensive use of de-icing salt on bridge decks and surface in the winter would cause steel corrosion due to the penetration of the de-icing salts through concrete surface.

2.3.2 Chemical Process

Concrete is very durable material that can withstand very harsh environment, but certain aggressive chemicals in the surroundings can cause concrete degradation. These substances must be in solutions or exceed the maximum concentration allowance, the following subsections discuss the types of chemical process: -

- **Carbonation**

There was no earlier knowledge of constant reaction happening inside the concrete which causes the release of carbon dioxide to the atmosphere. This recent discovery has made concrete unfriendly to the environment and unsustainable construction material. This process is triggered when concrete is exposed to carbon dioxide in atmosphere, usually the process is slow and insignificant, but if it accelerated due to variable factors, this could cause in reducing PH level which makes concrete useless protector of steel and eventually steel corrodes leading to structural failure. If PH level get below 10, then passivity layer is destroyed subjecting the steel to corrode (Saetta, Schrefler & Vitaliani 1993). Further discussion on carbonation process is found in Papadakis, Vayenas & Fardis 1989, Houst & Wittmann 2002 and Houst & Wittmann 2002

- **Sulphate Attack**

Bridges are usually exposed to sulphate through soil which makes substructures members such as foundation and piers the most exposed members for this type of attack. The reaction occurs when sulphate ions which mostly comes from external source reacts with cement paste components, calcium hydroxide and calcium aluminate hydrate to produce ettringite, gypsum or thaumasite that has larger solid volume which causes internal pressure which leads eventually to strength loss, degradation and spalling of RC bridges (Marchand, Oder & Skinny 2003). Sulphate attack is critical problem because it can cause a serious damage to bridges foundation, so some scholars have provided a good study on the subject ((Neville 2004), (Collepardi 2003)

- **Alkali-Aggregate Reaction(AAR)**

Alkali -Silica Reaction (ASR) is the most common alkali reaction inside the concrete. This type of reaction happens when aggregate contains silica which reacts with the alkalinity of cement to produce gel that expanse and causes problems for concrete. This was revealed by study by (Hobbs 1988). The expansion has no area to go therefore it would cause inside pressure that leads to cracks and spalling eventually. More information on the subject can found in (Swamy 2003).

Alkali-Carbonate Reaction happens with Dolomite in reactive carbonate rocks react with cement alkalis to produce calcite and Brucite. The reaction exposes clay minerals that tend to absorb water and expand which cause cracking (West 1990)

2.3.3 Steel Corrosion

Reinforced concrete structures deteriorate mostly due to corrosion of reinforced steel embedded in the concrete. Steel is brone to rust and that is why its embedded inside concrete to protect it from the air and water exposure. The alkalinity of cement plays the role of protector of steel to compensate for concrete low tension resistance. The relationship between steel and concrete is complementary. The corrosion process is electrochemical process which takes place because of existence of cracks that allows the penetration of chloride ions in water and with the existence of oxygen the steel begins to rust. Also, low level of PH of cement would shift the protecting environment to an aggressive one leading the steel to corrode (BRE ,2000). The outcome of corrosion would expand the length of the bars which would burst and break the concrete. Moreover, it would decrease the cross-sectional area of steel which automatically reduces the tensile strength. All these results would lead to structural failure. Many scholars have explained the steel corrosion causes and effects such as Almusallam (1996) and Cabrera (2006). The ingress of chloride ions through concrete due to de-icing salt cause steel corrosion in the cold weather countries (Neville, 1995)

The above-mentioned causes for deterioration are the most common and well-known types, However, there are other degradation causes for RC such as abrasion/erosion, fire and heat, volume changes, overload, and surface defects

2.4 Service Life Models

The factors accompanied with deterioration process has been discussed. Now, realizing the stages of bridge deterioration or the period it will sufficiently serve as infrastructure element would be very beneficial for the economy and community. The service life of concrete structures is the time which comes after the construction and when all the members exceed or meet the minimum requirement when routinely maintained (Masters and Brand 1989). The positive outcomes of establishing a service life model of RC bridge is worthwhile the efforts undertaken to do so. In recent years, the deterioration issue with RC bridges has become a major and serious topic in civil engineering. Bridge Management system (BMS) was established to gather information about inspection and maintenance of bridges. Many countries use historical data to build deterioration models to predict the life cycle cost. RC bridge deterioration has two phases; initial phase where material weakening and structural fault are not noticeable. The propagation phase is when deterioration commence and loss of function occurs (Rostam 2006).

There are many models built for deterioration process, nevertheless most of reliable ones fall into two different approaches, the deterministic model and the probabilistic model. These two models have been used for many years and each one has advantages and disadvantages. The following sections discuss in detail both approaches.

2.4.1 Deterministic Model

It is one of the deterioration bridge models that are considered direct and easy to build. It deals with certain and known variables. For example, adding two numbers and reaching a sum of definite result (Delkelbab et al 2008). As a result, the RC bridge performance is certain and determined with known final value. The performance of bridge in the model is achieved by applying a formula which describe the performance throughout its service time.

Numerous studies have been conducted to describe the deterministic modelling for bridges. These studies illustrate the relationship between factors affecting the deterioration and the deterioration age. Usually its shown as common statistical calculations for instance; mean, standard deviation, regression. The most used deterministic model is the factor method because of simplicity and direct way of applying the variables and receiving a reasonable predicted result. Several renowned researches contributed to deterministic modelling such as; Nang-Fei Pan et al (2009), Nireki (2002), Yanev (1996, 1997, 1998), Madanat et al (1995), Veshosky et al (1994), Jiang and Sinha (1989). All of these studies dealt deterministically with factor conditions and ignored random errors

Factor method is one of the most known and used deterministic models. Due to its simplicity and many factors consideration, it has become a very familiar model of service life. Several studies included factor methods for deterioration modelling such as Aarseth et al (1999), Hovde (1998 & 2002) and Abu Tair (2002). This method is an equation with factors to get the final service life of the bridge. Reference service life is multiplied with seven factors to have the estimated service life as shown in the equation 1

$$ESL = RSL \times A \times B \times C \times D \times E \times F \times G \qquad \text{(Eq.1)}$$

where A = quality of components

B = design level

C = work execution level

D = indoor environment

E = outdoor environment

F = in-use conditions

G = maintenance level

- **Disadvantages**

Obviously, a determined method of modelling the service life of a structure has a lot of shortcoming. Like any engineering problems, there are random and unknown variables that should be considered in the process and the deterministic model completely neglect these factors. According to Agrawal and Kawaguchi (2009) these types of models ignores the uncertainty due to the inherent stochasticity of infrastructure deterioration and the presence of unobserved unknown variables [(Madanat et al, 1995), (Jiang & Sinha, 1989)]. Furthermore, these models don’t provide any regard to maintenance process due to the difficulty and inconsistence inputs which these models don’t have a room for it (Sanders and Zhang ,1994). Also, the outcome is an average describing the deterioration rate, thus there is no consideration for the other condition status, hence the present and the old conditions [(Shahin et al,1987), (Jiang & Sinha ,1989)]. Another detriment point of these models, is the lack of interconnection of deterioration status between the bridges members (Sianipar and Adams ,1997). In another word, these models can barely estimate an accurate service life for a bridge.

2.4.2 Probabilistic Model

This kind of model use the probabilistic approach in dealing with deterioration process. Which means dealing with uncertain and unknown variables to predict the service life. These types of models have two main approaches which are state-based model and time-based model (Mach& Madanat,2001). Similar to deterministic models, they use statistical tools to present the data. For example, taking an average of several figures due to the uncertainty about deterioration behaviour [(DeKalb, 2008), (Ng S – K and Mosses,1998). Markov chains and semi Markov procedures are state-based type were the model describes the probability of transition between one condition to another in discrete time, assuming the deterioration process depends on a set of explanatory variables such as age, climate, traffic and etc. Markov Chain Models is used in many studies and research (e.g. Li, Sun and Ning, 2014). Nevertheless, multiple researches compared Markov chain with other methods such as Weibull distribution and the later methods results were better such as the study performed by (Agrawal, Kawaguchi and Chen, 2010). Time based models present the time distribution of the time taken by structure to change its condition from one to another. A set of arrays of variables are used for this process such as environmental exposure, design attributes and maintenance schedule. These types of models were used in studies like Mauch and Madanat (2001) and also by Noortwijk and pandey (2004).

The most used stochastic deterioration model is Markovian model. They are used in modelling different type of infrastructure elements [(Morcous et al , 2003), (Scherer et al, 1994) and (Micevski et al, 2002)]. Many BMS use Markov models due to their capability to capture time dependence and uncertainty of bridge deterioration prediction [(Dekalb, 2008) and (Marcos, 2006)]. In addition, their simplicity to use and sufficient computational model has made them one of the best models to use. Various studies demonstrate that Markov chain process has memory loss term, where only the current status is used in prediction as discussed earlier [(Dekelbab, 2008) and (Ng S-K & Mosses, 1998)]. On the other hand, some researchers have concluded this to be advantage towards their application.

Markovian-chain models can predict various condition transitions and changes through time for the structures components, their ability is derived from probability cumulative damage concept. Their concept is by accumulating probability and defining discrete condition from one states to another over several time discrete intervals, thus these models are performance prediction through the bridge service life. [(Marcos, 2006) ; (Ng S –K & Mosses, 1998) discusses the transition probabilities which are presented by matrix (nxn) called the transition probability matrix P, where n is the number of possible condition states. Each element (pi,j) in this matrix represents the probability of the bridge member condition. The bridge states will change from condition i to j during a particular time interval called transition period. when the initial status vector P(0) which presents the current condition of the bridge is known, the future condition vector p(t) at any number of transition periods t can be obtained as follows:-

P(t)=p(0)xpt

Where,

$$P = \begin{pmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,j} & \cdots \\ P_{2,1} & P_{2,2} & \cdots & P_{2,j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \ddots \\ P_{i,1} & P_{i,2} & \cdots & P_{i,j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \ddots \end{pmatrix}$$

$P\ (Xt+1 = it+1 \mid X0 = i0, X1 = i1, \ldots, Xt = it)$
$= P\ (Xt+1 = it+1 \mid Xt = it)$

Linear regression method is the mostly used to generate transition probability matrices. According to Marcos (2006), these linear regression functions can't provide adequate degradation process. That's why another method is proposed which is the Poisson regression model or negative binomial model. More discussion on this method can be found in [(Hawak and small , 1998), (Thompson et al ,1998) , (Chase and Gasper, 2000), (Vassie, 2000), (Racutanu & Sundquist, 2002), (Morcous, 2006) and (Linos, 2007)].

- **Disadvantages**

Probabilistic models succeed in considering some type of uncertainty in the modelling and include the present condition of the infrastructure facility in the analysis. Nevertheless, these models suffer from the legitimate question of service life prediction. Agrawal and Kawaguchi (2009) have discussed some weaknesses of probabilistic models, for example; these models predict the future condition of the bridge by only considering the current condition without giving any reference to the historical one, which is unrealistic (Madanat et al, 1997). Moreover, the connection of different bridge members for deterioration process is ignored (Sianipar and Adams ,1997). Also, the maintenance time and input are also ignored in these types of models similar to deterministic approach. Therefore, these models only count two types of state based shifting either stay the same or move to worse condition (Madanat and Ibrahim ,1995). In addition, time discrete intervals and constant bridge population can present the probabilistic model as impractical (Collins, 1972). Moreover, these models don't provide any regard to region-specific type which could have effects on the deterioration. Also, Transition probabilities are usually derived through linear regression with a large amount of data, which is not the case in most highway agencies. In a study conducted by Wellalage, Zhang and Dwight (2015) Markov chain Monte Carlo simulation technique is used with special algorithm for deterioration modelling of railway bridges in Australia. The results indicate improvement over the Markov chain Probability Matrix

Chapter 3: Literature Review of Artificial Neural Networks

This chapter discusses artificial neural networks development through the years and their usage in bridge degradation modelling. Artificial Intelligence is explored briefly since ANN is part of the discipline. This section includes the basic terminology of ANN, the origins, and the diversity of this field

3.1 Artificial Intelligence

A.I is computer science field that is concerned with imitating the human intelligence and behaviour to make decisions and solve problems. This new area of science had started at 1950`s and came back in 1980`s with huge advancement and revolutionary ideas. Artificial Intelligence emanated from diverse science fields that complete each other. These fields are but not limited to neurophysiology, cybernetics, psychology, mathematics, linguistics and computer science (Lu, Chen & Zheng 2012). A.I techniques is divided into two types which are the Expert system and machine learning. Expert system is a system that use reasons based on knowledge which evaluate the data by using if-then rule. Example of Expert System techniques is knowledge based system (KBS). The other method, machine learning uses statistical and algorithm approach to solve problems (Kobbacy 2012). The goal of developing Artificial Intelligence is to replace human intelligence with machine to solve complex system and large scale problems which changes over time. Some of ML techniques are Genetic Algorithm, Fuzzy Logic and Artificial Neural Networks. These methods are used in solving engineering problems which considered complicated. Deterioration models and maintenance management are very complicated ones that has a lot of changing variables. That's why the interest of developing artificial techniques for civil engineering fields has increased recently [(Kobbacy et al 2007), (Kobbacy 2008)]. In this research, machine learning technique artificial neural network is used for the degradation modelling. [(Shi & Zheng 2006), (Russell & Norvig 2010), (Arel, Rose & Karnowski 2010), (Michalski, Jaime & Mitchell 2013),(Chen et al 2015)] are relevant research and studies on Artificial Intelligence and engineering applications.

3.2 Artificial Neural Network (ANN)

ANN logic is derived from the human brain neural cells function and how these cells are connected to solve complex issues. Neural networks can recognize patterns, classify data, and approximate the solution for a complex non-linear function (Haykin 1999).

In 1943, the first concept of artificial neural network was developed by neuroscientist and logician, McCulloch and Pitts, respectively. The interest in research and development for ANN spread across the scientific community. However, it was not until the mid of 1980`s where new ideas and concepts flourished. The concept of ANN works by learning the relation between the independent and dependant variables, where the network is provided with input and targets in order to be trained for future prediction on similar manners. The result of ANN is called outputs which is compared with the targets to evaluate the Network performance. Neural network has many components and elements that differ in each case, however, there are standard parameters that every ANN contains such as; neurons, weights and biases of network, hidden layers, output layer, inputs and outputs. These parameters can differ in values, number and order therefore there are no universal or standard design for ANN. Neural Network can be designed in countless methods and shapes to fit in different types of function and systems. The matter of capability to design a good ANN comes from tedious procedure of trial and error (Marwala & Patel 2006).

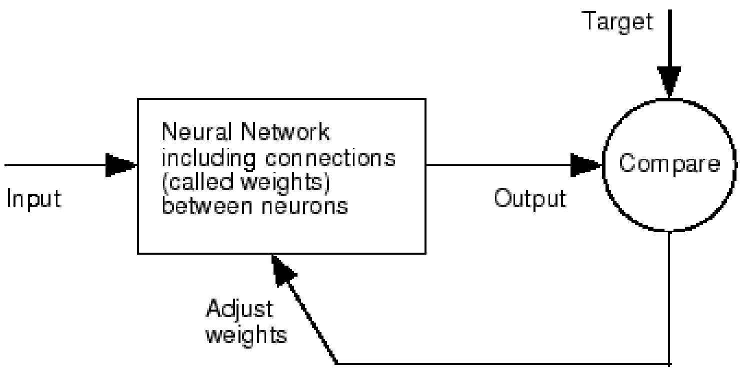


Figure 1: Diagram of Neural Network Process

Artificial Neural Network is adaptive and self-driven that requires no prior assumptions to the system before designing, which makes them adequate for random and complicated data. The training is what makes neural network more sufficient to predict solution for the complex system. With several training time, ANN could make a calculated and educated guess. All these features of neural networks make them good enough for estimating the deterioration age for concrete bridges.

In recent years, the design and analysis of Neural Network has become very wide due to huge computer processing and memory. . Moreover, ANN process can be described as black box, because no one can fully understand how the results was developed and how to investigate the process if the results are good or bad.

There are two main methods to improve the performance of ANN, the first method is called growing or constructing where neurons is being added until the network has satisfied certain criteria. The second method is pruning where the Neural Network is designed complex and then reducing the elements to become simpler. The above two ways are suggested by Song & Peng (2011) to avoid "over fit" or "under fit"

3.3 Neurons

Computational units that are fundamental for neural network structure. These neurons job, is to receive the input or external source information and process it to the output layer. A standard neural network has multiple neurons arranged in layers and attached to each other to form an interdependent network. These processing units are nonlinear, bound function and parametrized as mentioned by (Dreyfus 2005). A neuron can have one or more input and one or more output. The neuron output is nonlinear results of inputs (Xi) weighted by synaptic weights (wi) and the application function (f) on the results.

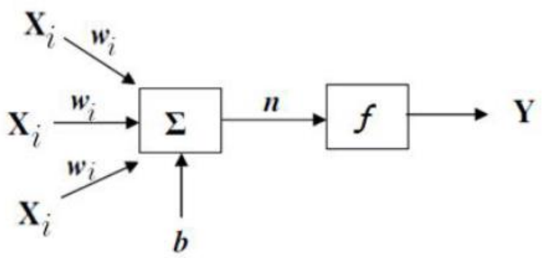


Figure 2:Basic Neuron

Each one of the neuron has a linked weight which present the significance of the carried signal. These weights are allocated according to experience gained by training. Also, a bias value of 1 is included with the input neurons (Gupta, Jin &

Homma 2004). Transfer function or activation function is applied to the weighted sum of the input and bias as illustrated in equation 2. This function limits the amplitude of the output of neuron

$$Y = f(wX + b) \qquad \text{(Eq.2)}$$

Transfer function can be linear or nonlinear, some of these functions include; purelin, sigmoid and hyperbolic as shown in figure 3

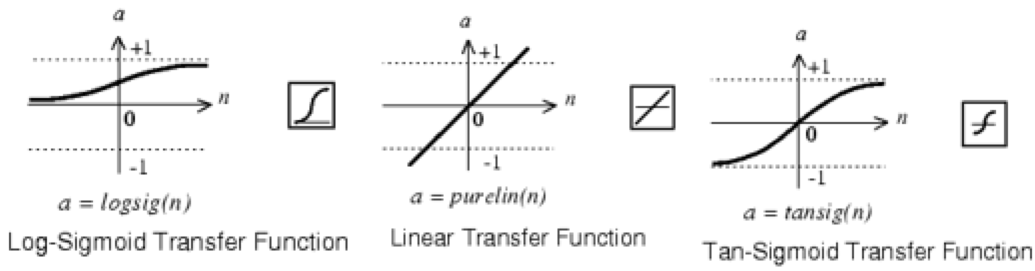


Figure 3: Transfer Function

3.4 Types of Neural Networks

Choosing ANN type depends on the type of system and data available to process. Different types of Neural Network exist, Nevertheless, depending on the action and desired target the network could be assembled in any manners. There are four categorises of ANN tasks; Fitting and approximation Neural networks, Pattern Recognition and Classification, Clustering Neural Network and Time Series & Dynamic Neural Network. Two main types of artificial neural networks exist, feed forward neural network and Recurrent neural network

3.4.1 Feed-Forward Neural Network (FFNN)

It is the most common and simplest type of NN, the concept revolves around providing the network with direct input and output to obtain the desired targets. The network simply designs a connection and relationship between the inputs and outputs. It is also called fitting Neural Networks, which derived from fitting a relationship between the Input and output. Each neuron in the feedforward Net has only direct connection to the neurons in the next layer. There is no feedback or recurrent neurons which comes from the output layer to the input layer (Kriesel 2007) & (Gurney 1999). According to (Hornik, Stinchcombe & White

1989)“standard multilayer feedforward networks are capable of approximating any measurable function to any desired degree of accuracy”. As illustrated in Figure 4, the inputs are fed cross the hidden layer to the output layer. FFNN can solve fitting and function approximation problems. In other words, its nonlinear regression relation between the inputs and the outputs (Hagan 2014). These type of networks can be optimized by different ways, for example, they can be a time delay function, if the input is delayed from entering hidden layer. There are different types of FFNN such as distributed time delay neural network (DTDNN) and Time delay neural network (TDNN).

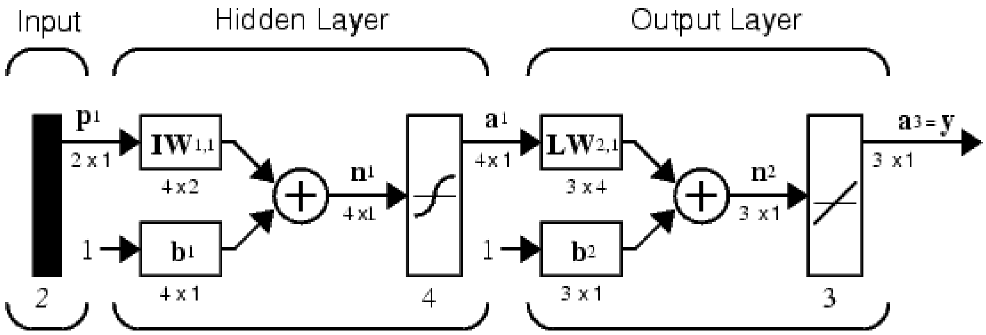


Figure 4:Feed Forward Neural Network Diagram

3.4.2 Recurrent Neural Network

This type of network has feedback or recurrent loop where the output of network is inserted back into the computational stage with the direct input. Unlike feed forward networks (Static networks), recurrent or dynamic neural network results depends also on previous output for analysis. This step develops a short term memory for network and provide it with dynamic modelling where the time or state sequence data affects the results [(Hagan 2002 &2014), (Kriesel 2008) and (Box 2008)]. Figure 5 demonstrates how the outputs are feedback with the direct input to hidden layers. Dynamic Neural networks are prediction tools in time series models. They are very powerful networks and exceed feedforward NN in the performance and results. Nevertheless, they are very complicated and nearly impossible to present the analysis mathematically. Examples of dynamic neural networks are; Nonlinear autoregressive exogenous Input neural networks (NARX), Hopfield and Elman Neural Network.

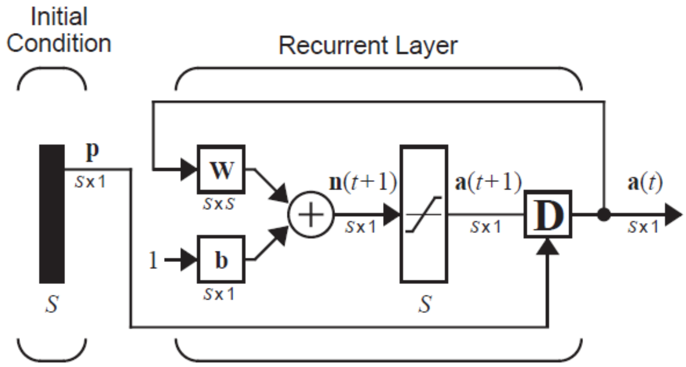


Figure 5: Recurrent Neural Network Diagram

Artificial neural networks are huge field with multidisciplinary aspects and what was discussed in this chapter relates only to this research which covers small percentage of information on neural networks. So, for more neural networks studies, the following published items is worth reading. [(Hagan et al 2014), (Box, Jenkins & Reinsel 2008),(Haykin 1999),(Gurney 1999) and (Fausett 1994)]

3.5 Back Propagation Algorithm

The common form of learning algorithm for neural network is backpropagation. There are different types of this algorithm but the simplest form is when the error function or the negative gradient decreases rapidly to update the weight the bias. A single iteration can be described as

$$x_{k+1} = x_k - \alpha_k g_k \qquad \text{(Eq.3)}$$

x_{k+1} is the vector of weight and bias, α_k is the learning rate and g_k is the gradient.

Backpropagation algorithm seeks the minimum error function by the gradient. In order to find the minimum gradient, a combination of weights must be used to reach the minimum error. At the initial training, weights are initialized randomly and then the gradient is used to compute the error function and correct the weights. This is done repeatedly until the error can't decrease any more. The most used error function is mean square error as written below

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (O - T)^2 \qquad \text{(Eq.4)}$$

O is the output of neural network and T is the target values. Although Backpropagation algorithm is usually used with neural network as learning method, it has two main setbacks. Slow learning speed and sensitivity to parameters are the two drawbacks for this algorithm. So, several modifications were done to overcome the problem and new types of backpropagation are developed such as Gradient descent backpropagation with adaptive learning rate of momentum coefficient (GDX) and Levenberg Marquardt(LM).

3.6 Artificial Neural Network in Modelling Bridge Deterioration

Bridge Deterioration is grave issue for civil engineering, since bridges are considered infrastructure facility, their effects are massive on society and economy. The structural integrity of many bridges especially the ones that are old or built in harsh and aggressive environment are crucial factor for public safety. Since estimating the deterioration age and the best maintenance time is not accurate, many research is conducted to develop a method good enough for deterioration model. According to Flood (2008), civil engineering community has developed an interest for research on the next generation of Neural networks (Lu, Chen & Zheng 2012).Bridge inspection is not adequate enough for what is required by BMS. Due to the lack of sufficient historical data, the current BMS that incorporate a deterioration model is incompatible (Callow et al. 2013). So, some researchers are exploring the use of ANN in Service life prediction. Lee at al (2010) suggest using ANN to improve BMS (Bridge Management Systems) by generating historical bridge condition from limited bridge inspection records. After generating the historical data, time delay artificial neural networks is then used to predict a long-term performance of the bridge structural members. Nevertheless, they encountered a contradicting value between the original historical data and the data generated by ANN-Backward prediction model. So, the researchers have decided to take the BPM values instead of the original. In continuation study, a new method to process the outcomes of BPM neural network to discard the random condition ratings to improve the deterioration prediction. Furthermore, Lee at el(2012) published another study of hybrid optimization method to filter the data from BPM model. This method seems to have generated better results for deterioration model.

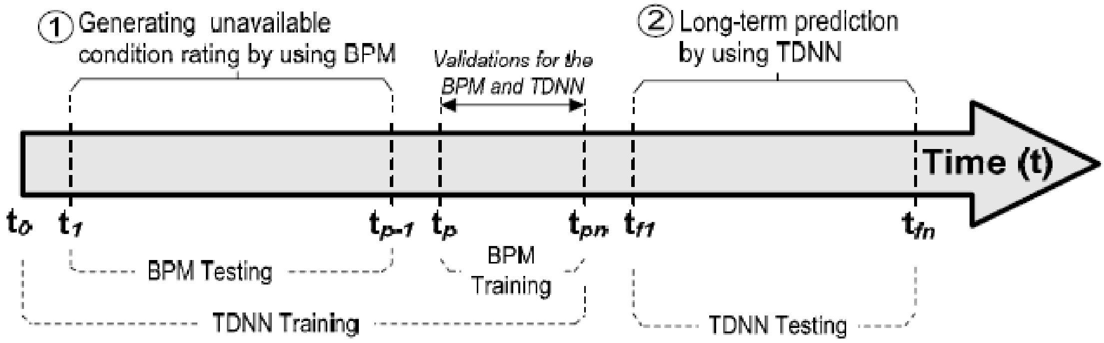


Figure 6:Time Delay Neural Network Prediction Diagram

In the last decade, the use of ANN in reliability analysis has emerged due to their capability for good approximation of the results with time consuming repeated analyses of Monte Carlo method. According to Hurtado, Neural Networks has shown the ability to examine uncertainty of one dimension in stochastic finite element problem. In study about bridge concreted decks and life cycle cost, a model of Artificial neural networks with genetic algorithm was used. The type of NN is a feed forward network with backpropagation learning function. The designed neural network has three layers with sigmoid transfer function for hidden layer and linear function for the output layer. The ANN-GA approach handled well the high computational complexity of Technology (Firouzi & Rahai 2012).

Another study conducted by Bu et al (2012), where integrated method for deterioration model used Elman Neural networks to substitute the regression function in predicting the deterioration patterns. The integrated method used the probabilistic time and state based models. ENN is incorporated in state based model to generate the bridge members condition rating. The study shows good results for ENN, nevertheless, the authors recommended more case studies to confirm the reliability of neural networks. Furthermore, in continuation study for lee at el (2010), Elman neural network has been used instead of time delayed neural network. According to this journal, TDNN has produced illogical pattern and irregular noise pattern, which caused poor training for the data. Thus, ENN as recurrent neural network has advantage over feedforward neural network. This research has provided a comparison between feedforward neural network results and recurrent network.

A multilayer perceptron feedforward NN is used to quantify the damage severity in bridges. The neural network is first trained for FEM (Finite Element Method) analysis and then the resulted were confirmed. The study acknowledges the advantages of using artificial neural networks with large accumulative data (Chun, Yamashita & Furukawa 2015). In Kabir et al 2008, MLP used as pattern recognizer and classifier for texture analysis to evaluate the bridge structural damage (Kabir, Rivard & Ballivy 2008).

Hung (2010) has developed ANN model for bridge deterioration where eleven factors are used as input and five condition state for output. Multilayer Perceptron with backpropagation is used to predict the condition state. Hung has used trial and error to determine the best number of hidden layers and hidden neurons. "The ANN prediction model reaches classification rates of 84.66 % and 75.39% for the training sets and the testing sets, respectively" (Hung ,2010). Furthermore, ANOVA is used to check the significance of maintenance history for condition states 1-2 and 2-3. In his study, Hunag claims that Markov Chain approach used by BMS is unrealistic and inaccurate for prediction of bridges deck deterioration and propose Artificial Neural Network with Multilayer Perceptron (MLP) as good tool for determining the deterioration rate and the best time for maintenance cycles. Furthermore, ANN used as pattern classification tool which categorize the inputs and output into similar classifications with utilizing Back-propagation tool to substitute for missing data. MATLAB programs were used and developed to construct the ANN prediction model.
Dang et al (2014) suggests using ANN in seismic fragile curves for highway bridges instead of the long exhausting computational using incremental dynamic analysis (IDA). The implementation of ANN is focused on the simulation of median value and standard
deviation of IDA curves at a given intensity level. They have used ANOVA to compare the results.

After reviewing literature, it is concluded that most of the ANN model for bridge deterioration studies are to be validated and more case studies needed. Furthermore, Feed forward neural network is widely used in deterioration modelling and their performance is robust for function approximation and pattern recognition. So, FFNN is used for bridge deterioration modelling in this research

Chapter 4: Data Analysis

In this chapter, the historical database of reinforced concrete bridges located in London is processed and analysed to turn the raw data into a logical and systematic input and target for neural network to process. Inspection records of deterioration occurred to these bridges would serve as the training and testing sets for ANN. Data Analysis is critical part of the research due to its direct impact on the outcomes.

4.1 Data Processing

Historical records of Inspections performed on more than 400 reinforced concrete bridges built in London, United Kingdom, between 1880 & 1930 is used in this study. The defects database is provided by [(Rigden, S.R., et al, 1993), (Rigden , S.R. et al, 1996) and (Mc Parland, C.B. et al, 2001). The first record of inspection was registered at the late of 1920s and continued till the 1980's. So, 60 years of recording the defect histories for four hundred bridges. Some of these bridges were inspected several times throughout the years and other bridges were only inspected once. Therefore, there is no pattern of inspection and recording. There are ten parameters which describes the details of inspection time and findings, as shown in Table 1

CODE	Bridge Type	In year	Fault	Size	Cause	Member	Exposure	Urgency	Age
TC003	Footbridge	1966	4	3	1	1	1	1	29
TC003	Footbridge	1971	5	1.5	3	1	3	1	34
TC004	Overbridge	1974	7	0	1	2	1	2	60
TC004	Overbridge	1987	8	0	2	2	1	2	73
TC005	Footbridge	1935	4	3	1	2	2	2	11

Table 1: Organization of The Database

In order to analyse the raw data, each item in table 4.1 must be reviewed. The first item mentioned in the database is CODE of the bridge. It is the name given for bridge to distinguish the inspection recording for each bridge. Every bridge is given a different code to expedite the inspection historical record retrieval. There are six types of bridges in this database such as; Footbridge , Overbridge and Underbridge. In-year refers to the year of inspection had occurred and the age parameter refers to the age of the bridge during the investigation

Five parameters in the database were coded with numbers to facilitate documenting the information by the inspection teams. These numbered parameters are Fault, Cause, Member, Exposure, and Urgency. Table 2 and 3 provide the decoding for the five parameters.

Fault/defect defines the type of defect that was observed during the inspection. Ten types of defects were recorded during the inspections, theses range between hairline crack to demolishing. Member parameter describes the type of member inspected in the bridges. These members were listed based on their structural task. Five types of bridge members are registered in the database, Flexural, compression, Joint, Parapet and other as shown in Table 2. From preview of database, flexural and compression members are the most frequent recorded bridge members. While performing inspection, engineers have indicated the cause of damage in the concrete, causes are shown in Table 2 as well. Another parameter monitored is the exposure condition of the built environment for bridges. The environmental exposure is defined in accordance with the conditions set out in BS 8110. This factor is very important in influencing the deterioration age for RC bridges. The last numbered factor is the urgency of repair, depending on the damage reflected on the bridge, engineers have assessed the necessity of repair. Some of these bridges need immediate rehabilitation while others do not require any repair at the inspection time.

M	Member Type	E	Exposure Conditions	C	Cause	U	Urgency/Repair
1	Flexural	1	Mild	1	Not Known/Define	1	Insignificant
2	Compression	2	Moderate	2	Early Age Cracking	2	Serviceable
3	Joint	3	Severe	3	Over-Stressing	3	Very Significant
4	Parapet	4	Very Severe	4	Impact		
5	Others	5	Extreme	5	Corrosion		

Table 2:Coded Parameters in the Database

Fault/Defects						
0	1	2	3	4	5	6
Defect Free	Hairline Crack	Single Crack, 1.5mm	Multiple Cracks, 1.5mm	Single Crack, 3.0mm	Multiple Cracks, 3.0mm	Cracks over 3.0mm
7	8	9	10	11	12	
Minor Spalling	Spalling, Exposed Reinforcement	Severe Spalling	Demolishing	Minor Repair	Major Repair	

Table 3: Defects Type

4.2 Data Analysis

The current dataset has huge and massive information about 400 bridges. So, Data Analysis is necessary step when handling a large quantity of information. The raw gathered data are scattered and random with many inadequate information. Therefore, the database has undergone extensive analysis to obtain the best information needed for estimating the defects age of concrete bridges. This step is vital for the using Neural Network and obtaining valid results. Since Feedforward Neural Network is selected for this research, the quality of the dataset would directly impact the performance due to function fitting analysis.

4.2.1 Bridge Type Analysis

The first analysis was to determine the total number of structures and their type. Six types of bridges and structures were inspected and recorded in the historical set. Not all the structures have equal number of occurrence, so it’s necessary to determine the number of each one and decide which will be excluded from deterioration modelling. Figure 7, shows the outcome of the analysis, Footbridge and overbridge has 160 and 100 bridges, respectively. These bridges have the highest recorded type, whereas under bridges, Gantry Bridge, Cover way and Wall has 78, 38, 28 and 10 records, respectively. Since this is the first parameter to be analysed and other parameters would be filtered, all the bridges and structures less than 100 records would be excluded. Therefore, only Footbridge and Overbridge are included for the deterioration modelling.

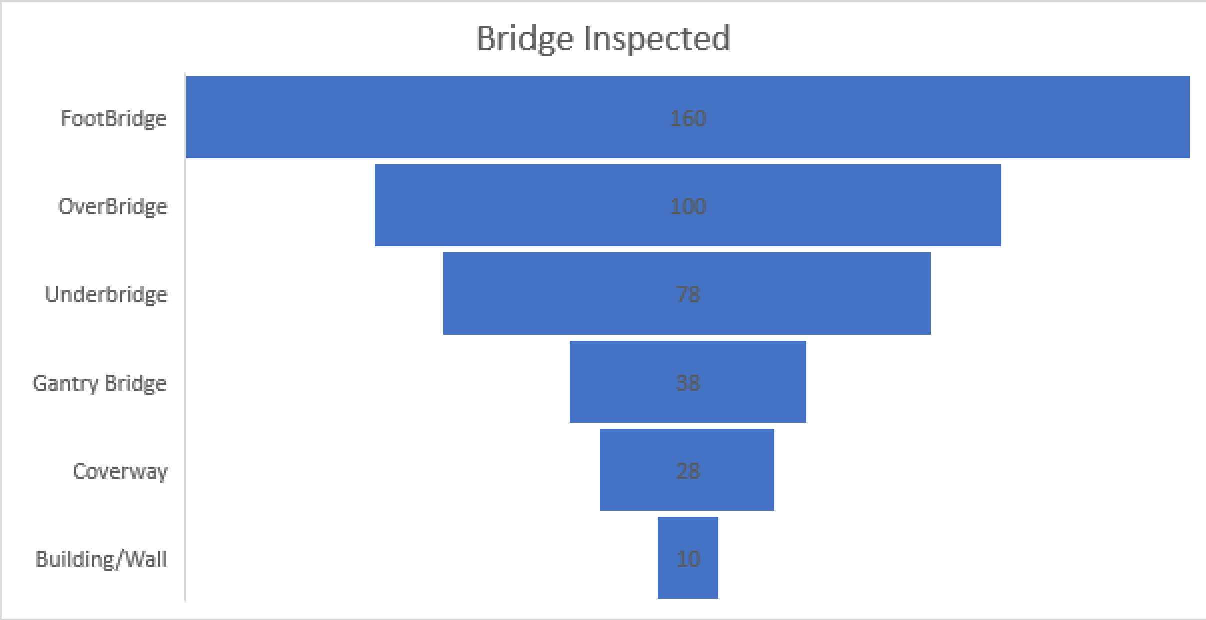


Figure 7: Bridge Type

4.2.2 Member Type Analysis

Five different bridge members were recorded in the database. The analysis of the records show that flexural and compression members were the most frequent ones as illustrated in Figure 8. Flexural has 39% of the total records and compression members has 31% occurrence, these two members will be included in the modelling. Parapet, Joint and other members are less than 20%, so they systematically filtered and excluded.

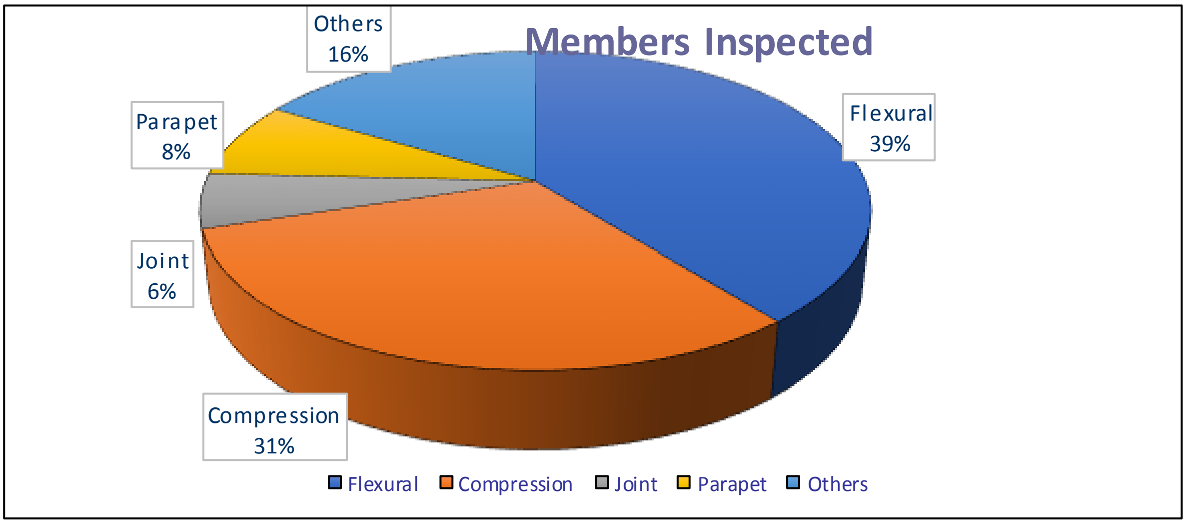


Figure 8:Member Type

4.2.3 Defects Analysis

This parameter is the most important one, since it indicates the deterioration stage of the recorded bridges. The inspectors recorded 12 different type of defects that range between no defects recorded to service failure. This study purpose is to model deterioration, so only the inspection records of first occurrence of defects are used in the analysis. So, the records which indicates no defects (coded Zero) were discarded. Also, the hairline Crack (coded 1) is also excluded because this type of crack is on the surface and doesn't indicate the commencing of deterioration.

Ten defects are left for the analysis and since its necessary to organize data, these defects were categorized into 4 condition states as the followings:-

1. Minor Cracking/Condition States 1 (Contains defects 2,3&4)
2. Major Cracking/Condition States 2 (Contains defects 5,6&7)
3. Spalling/Condition States 3 (Contains defects 8& 9)
4. Service Failure/Condition States 4 (Contains type 10,11 & 12)

After grouping the defects into four main condition states, Figure 9 demonstrates the analysis outcome which shows that Major Cracking/Condition States 2 has the most records followed by Minor Cracking and Spalling. Condition state 4 or Service failure is the least recorded. All the four defects group are included in the deterioration modelling because of their importance.

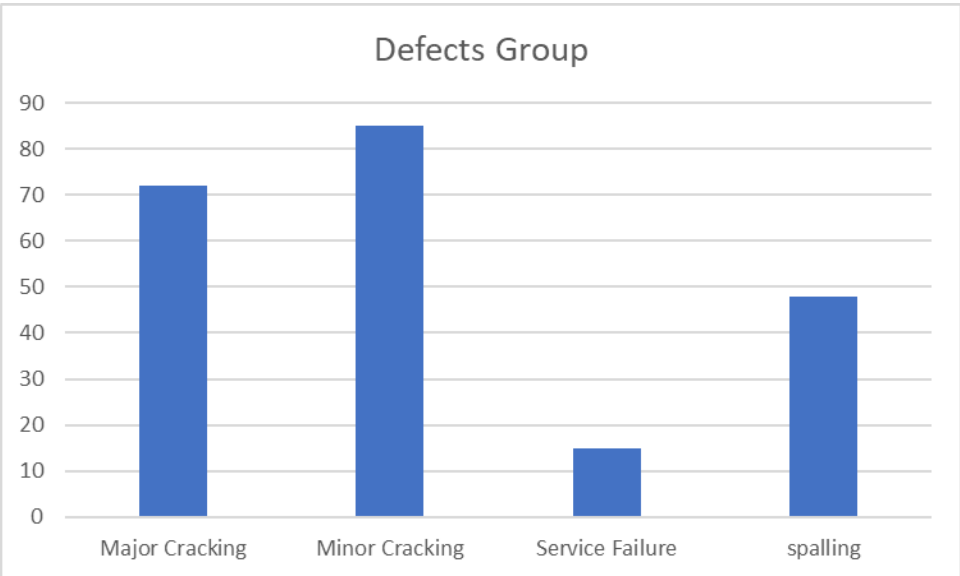


Figure 9:Defects Type

4.2.4 Exposure Conditions

Figure 10 illustrates the condition of exposure for the bridges. Moderate condition is the most recorded one followed by mild conditions. Severe exposure is the least condition in dataset. Since there are only three types of environmental exposure and this factor is vital for the deterioration modelling all of three types are considered for ANN input.

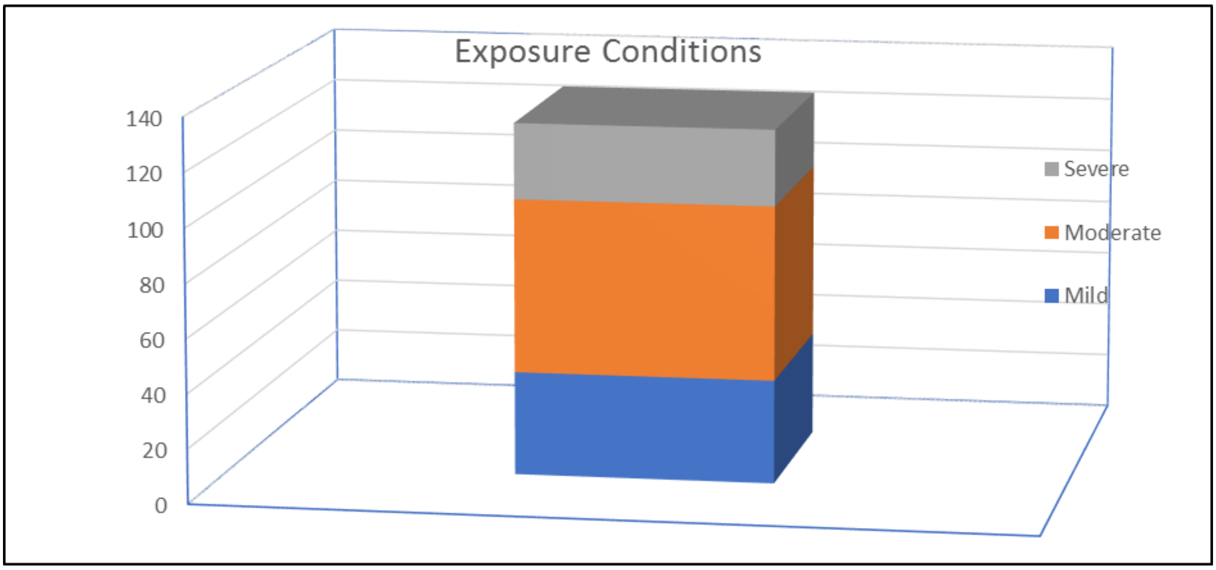


Figure 10:Exposure Conditions

After examining the database, four main factors are used for deterioration modelling using artificial neural networks. Bridge type, member type, exposure condition and fault are used as input for ANN. These factors are also used in previous bridge deterioration studies e.g. (Radomski 2002; Scherer and Glagola 1994; Agrawal et al. 2009; Morcous et al. 2002) Although, the earlier studies have addition factors such as the material type and the number of spans, these data are not available in this database.The age of inspection would be the target variable in which the neural network will be trained to achieve. Urgency of repair parameter is not included in the analysis because it does not contribute to deterioration process. So, it is not needed to serve as input for NN or as an output

4.3 Deterioration Scenarios

It is necessary to have detailed insights about the Neural network input, therefore a comparison between the different deterioration scenarios is performed. FFNN is used for this research, which is a fitting and approximation function, it is very necessary to obtain the deterioration information from the original data. After processing and filtering the data, four main factors are selected which means 48 scenarios (2 bridge types x 2-member types x 3 exposure conditions x 4 condition states) are available for deterioration modelling.

The average of the counts was taken to enable the deterioration comparison. From the historical data, footbridge deterioration age or service life is higher than overbridge. This is without considering the exposure type or the member type, as shown in figure 11. Also, the spalling defect for footbridge occur in time later than overbridge spalling defect. Both footbridges and overbridges has equal average of occurrence age for major cracking. Only in Minor cracking defect where overbridge average age exceeds the footbridge age.

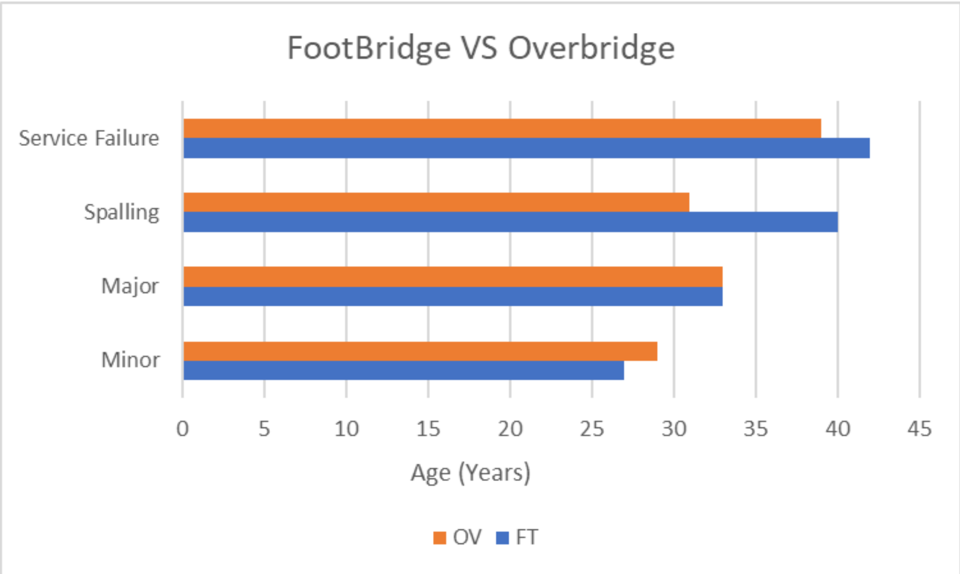


Figure 11:Footbridge vs Overbridge

Then, the member type factor is considered in the modelling, flexural and compression members. For footbridge, the compression members deteriorate after the flexural members for all the defects type as shown in figure 12. Spalling defect for compression members has an average of 50 years to occur while the service failure has a less than 43 years to occur. This is another demonstration that the database has missing information especially for service failure/condition state 4.

Overbridge with flexural members has better deterioration age than compression member for service failure and major cracking defects. While for minor and spalling defects the occurrence of deterioration for compression member is later than the flexural members.

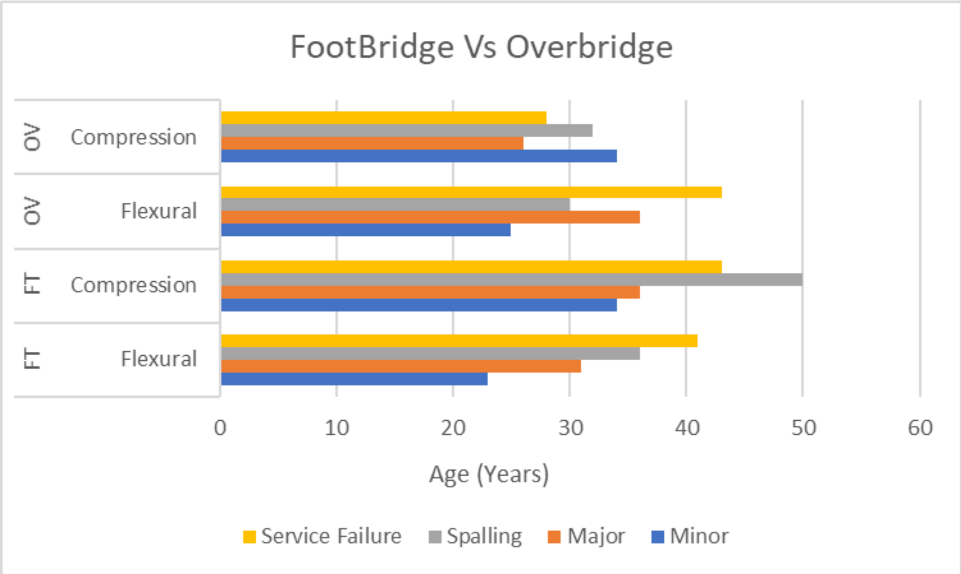


Figure 12:Bridge Type and Member Type

The last factor provided in the database to have impact on the deterioration age is the exposure conditions. As mentioned earlier, three types of environmental exposure are available; Mild, Moderate, and Severe. Figure 13 , illustrates the modelling of bridges with environment exposure factor. For footbridge, severe environment has recorded the highest service life, which means the lowest deterioration rate. Condition state 4/service failure records were not available for sever exposure. This shouldn't be the case , severe condition should have the highest deterioration rate. There are no other information in the database that can provide a reason for this result. So, its either the bridges had a very good design to combat the severe environment or there are missing information in the database. For this study, the first reason is assumed to be right. Mild exposure condition state 4 occurs after the moderate conditions. But the other three defects age for moderate exceed the mild one. Nevertheless, overbridge does not follow the same pattern of footbridge. Service failure for mild condition occurs after moderate and severe condition. For the other defects, severe and moderate condition, the deterioration age occurs after the bridges exposed for mild environment.

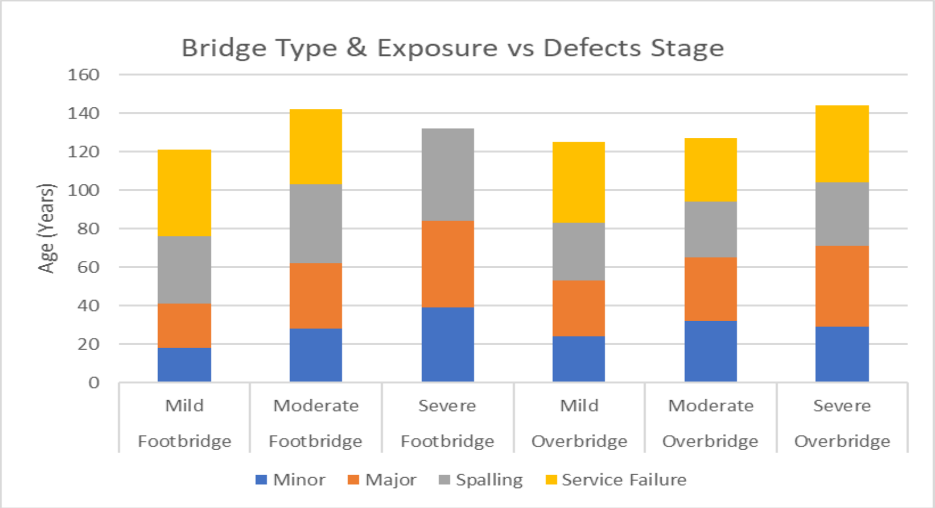


Figure 13:Bridge Type & Exposure

- **Footbridge**

Table 4 illustrates the defects age for footbridge with considering all other parameters. Two scenarios for service failure in severe environment are not available due to missing and inconsistent information. Compression members with severe exposure have the lowest deterioration rate. Compression members exposed to moderate and severe environmental conditions have higher defects age and lower deterioration rate than flexural members. On the other hand, flexural members in mild exposure has lower deterioration rate than compression members. In general, compression members have higher resistance to degradation

Exposure	Member	Minor	Major	Spalling	Service Failure
Mild	Flexural	20	27	33	52
Moderate	Flexural	22	31	36	25
Severe	Flexural	36	43	45	-
Mild	Compression	15	13	42	25
Moderate	Compression	39	42	52	53
Severe	Compression	45	55	55	-

Table 4:Footbridge Deterioration Scenarios

- **Overbridge**

Table 5 demonstrates overbridge defects age considering the other parameters. Service Failure for compression members for the three exposure conditions is not available due to missing and inconsistent information. Compression members in severe environment deteriorates faster than moderate and mild. This follows the expected pattern of degradation when the exposure is severe, the deterioration rate increases. Compression members exposed to moderate environmental conditions do not follow the expected pattern of deterioration. For flexural members, the severe conditions have the lowest deterioration rate followed by moderate and then mild.

Exposure	Member	Minor	Major	Spalling	Service Failure
Mild	Flexural	27	31	31	31
Moderate	Flexural	22	34	29	29
Severe	Flexural	30	48	30	30
Mild	Compression	20	23	25	-
Moderate	Compression	48	27	30	-
Severe	Compression	27	30	35	-

Table 5:Overbridge Deterioration Scenarios

After the analysis, 220 rows of Historical data are ready to be used for neural networks modelling. The data is still scatter and have degree of randomness because some of the same factor scenarios do not have a similar corresponding defect age. Forty-three degradation scenarios are used for the deterioration modelling.

Chapter 5: Methodology

The aim of this research is to estimate the deterioration age of RC bridges using ANN. Therefore, in this chapter, the process of building a suitable artificial neural network for deterioration is explained in detail. Furthermore, to understand the parameters effects on ANN performance, design of experiment is used instead of at a time factor approach.

5.1 Research Statement

The purpose of this study is to explore the performance of Artificial Neural Network in estimating the defects age for concrete bridges given historical records. Moreover, using design of experiment to test the chosen variables on ANN performance. Deterioration modelling for concrete bridges is huge field with several modelling methods as discussed in chapter 2. Nevertheless, most of the modelling methods are inadequate in dealing with stochastic variables as mentioned in literature review of chapter 2. Thus, artificial intelligence is employed for degradation modelling. One of the most common techniques in AI is artificial neural networks, similar to the concept of brain neural. More on ANN origin and types discussed in Literature review of chapter 3. Neural network is trained and tested on sample of data for function fitting using Mathworks software, MATLAB.

5.2 Neural Network Design

ANN has many types and factors to choose while building the network. They can range from simple architecture to a very complicated one. There is a vast variety of ANN design but all of the neural networks have the same steps for building the model, these steps should be adhered to ensure adequate design. Data collection and Data pre-processing is the first step in creating the network. Then, creating and configuring the network paradigm. After building the network, training and validation steps are final steps in designing the artificial neural network in this research paper. The following sections discuss in details the building of ANN

5.2.1 Data Collection

Historical records of Inspection performed on 400 concrete bridges built in UK Between 1880 &1980 is used in this study. More details were mentioned in chapter 4. The collected data were analysed to obtain the most valid variables to serve as input for ANN. Input data is very important because it impacts the generalization ability of ANN. In this study, the acquired bridges database has several parameters to investigate for the model, such as the exposure condition, defect type, defected member type and bridge type. These factors are used as input data to develop a neural network model as shown in table 6, while the age of bridge based on the recorded defect is used as the target. Forty-three combinations of deterioration scenarios are available for the analysis. Most of these combinations have several repetitions, nonetheless, many of these input repetitions do not have the same response variable (Targets). A total of 220 rows of input and targets are used for training and testing of neural networks.

ANN Input				ANN Target
Bridge Type	Member Type	Exposure Condition	Defect Type	Age of the Defect

Table 6:Inputs and Target for ANN

5.2.2 Data Pre-Processing

Pre-processed data means to shift the input and output values to simpler and easier format for NN to deal with. It is uncommon to insert raw inputs and targets to ANN directly; instead, pre-processed data is used since it tends to assist ANN learns patterns better (Zhang, Eddy Patuwo & Y. Hu 1998). This is recommended when performing analysis through neural networks to reduce noise, detect patterns, and flatten data distribution to assist ANN in learning relevant pattern. So, the data presentation is essential in designing a successful network. The available data is nominal variables and to inserted into Neural Network in MATLAB, these values needed to be converted to numerical values. The values are categorical, so each set on these inputs were coded to numerical values, the conversion was like this for exposure condition: Mild Exposure=0, Moderate Exposure=1, Severe Exposure=2. For the type of bridge, there are two types footbridge and overbridge, so the coded numbers are 0 and 1, respectively. Also, member type is coded similar to bridge type, 0 and 1. The last input parameter, the defects type was coded from 1-4, starting with condition state 1=1 till condition state 4=4.

The age of defects which is the target for NN was also pre-processed by keeping the values between 0 to 1. This was done by dividing all ages by the largest recorded age which is around 60. This step was to keep the mean square error for neural network small

5.2.3 Neural network paradigms

Artificial Neural Networks can be built in unlimited number of ways. ANN architecture could be designed in many shapes and types relying on many factors, such as; the number of input neurons ,number of output neurons, number of hidden layers, number of hidden neurons, learning algorithm, transfer function, , types of connections between all these neurons and etc. Nevertheless, there are four important parameters to design a network. Each one of these parameters would have two options for the neural network to be able to conduct design of experiment. DOE would be discussed in the coming section. The followings discuss the four factors options:

I. Hidden layers

These layers are important because it's the process center of neural network , its where the learning and generalization ability occur. Usually one or two layers are enough to train medium size data. Moreover, the nature and type of data can impact the suitable number of hidden layers. The more the complicated the data is, the more hidden layers needed. However, more layers might increase the risk of over-fitting, where neural networks memorizes exact targets instead of learning how to estimate them. Commonly, one layer with adequate number of neurons is enough for good fitting and approximations. Therefore, one and two hidden layers are selected in designing ANN

II. Neurons

There is no rule or equation to calculate the required number of hidden neuron, each scenario has their own number. Trial and error can indicate the adequate number of neurons. The issue of choosing a suitable number of hidden neurons is the over fitting problem when selecting large number of neurons for the network. According to Hagan et al (1998) the training sample number, m, should be larger than the adjustable parameters where n is the input values number and M is the number of hidden neurons as shown in equation 6.

$$(n + 2)\, M + 1 < m, \qquad \text{(Eq 6)}$$

For this research 10 neurons and 20 neurons are chosen for design of NN, since the training sample is 200, these numbers fall within the range of Hagan (1998) suggestion.

III. Output Layer Transfer Function

The output function job is to refine the data coming from the hidden layers before releasing the output results. There are three main types of transfer functions used in the output layer. Pure-linear and sigmoid functions are used frequently due to their continuity feature. The Hyperbolic Tangent sigmoid (Tansig) and pure linear functions are selected for this study. Table 5.2 shows the transfer functions. According to Hagan et al (1998), having a Tansig as function in hidden layer and Purelin in output layer is the universal design for fitting or approximation case. So, for hidden layer the hyperbolic Tangent sigmoid function is used as transfer function. However, for the output layer, both of Sigmoid and liner function would be used for designing ANN

Name	**Function**	**MATLAB Name**
Linear	$a = n$	**Purelin**
Log-Sigmoid	$a = \frac{1}{1 + e^{-n}}$	**Logsig**
Hyperbolic Tangent Sigmoid	$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$	**Tansig**

Table 7:Transfer Function

IV. Neural network Learning Algorithm

The process of training ANN iteratively feeding it with inputs and presenting it with correct answers. After the training process is over, the ANN is meant to provide a good generalization. The main aim of training is to reach the global minimum of the error function. There are different types of training/learning function such as, Levenberg Marquardt, Quansi-Newton, resilient back-propagation, Bayesian Regularization and Scaled Conjugate Gradient and etc as shown in Table 8. These functions were tested by Mathworks and concluded that Levenberg Marquardt (LM) and Gradient Descent BP (GDX) are the best learning functions. So, these two functions are selected for NN design

Function name in MATLAB	Training algorithm
Trainlm	Levenberg-Marquardt back-propagation
Trainbr	Bayesian Regularization
Trainbfg	BFGS Quasi-Newton back-propagation
Trainrp	Resilient Backpropagation back-propagation
Trainscg	Scaled Conjugate Gradient back-propagation
Traincgb	Conjugate Gradient with Powell/Beale Restarts back-propagation
Traincgf	Fletcher-Powell Conjugate Gradient back-propagation
Traincgp	Polak-Ribiére Conjugate Gradient back-propagation
Trainoss	One Step Secant back-propagation
Traingdx	Variable Learning Rate Gradient Descent back-propagation
Traingdm	Gradient Descent with Momentum back-propagation
Traingd	Gradient Descent back-propagation

Table 8:Learning Algorithm

5.2.4 Evaluation criteria

To examine and evaluate the performance of neural network outcome, several performance functions can be used, such as; Mean Square Error (MSE) and Sum of Square Error (SSE). Nevertheless, for fitting function, MSE is typical used as evaluation tool for ANN performance. Also, mean square error is used as response variable for experimental analysis. In addition, regression and error histogram is good indicator of the performance of the fitting network.

5.2.5 Training, Testing and Validation

The neural networks inserted data is used in three different sections to complete the cycle of training and testing. ANN divides the fed information into training, testing, and validation group. The selection of each group is random and with each new training process different data is selected to these groups. Training set is the largest and is used to train the ANN to learn data patterns. Then, a smaller testing set is selected with smaller portion to check the generalization ability of the newly trained network. lastly, the validation set is for performance double check of network. The training set takes the biggest portion of the data to give the network enough data to learn and train. There should be a balance between having enough sample size to evaluate the network and enough remaining data for the other two sets. It is recommended to use and 90% to 70% for training data and 30% to 10% portion for testing and validation sets. To provide ANN a sufficient data for learning, we adopted the 70-15-15 division set.

5.2.6 Training Parameters

After building ANN, set of parameters are available to control the training process for neural networks. These parameters influence neural network learning process, therefore it's important to choose the adequate values. There are four main training parameters that affect the training process for ANN; Epoch, gradient descent, validation checks and learning rate. The values for these parameters are fixed for all the experiments and their iteration. Table 8 shows the training parameters values.

i. Epoch: iteration of training of neural network, when a full loop of backpropagation is completed.
ii. Gradient Descent: the training of neural network will stop once it reaches the minimum value of gradient descent
iii. Validation Checks: the number of times the validation error will be checked before the training stops
iv. Learning rate (Mu): As explained in chapter 3, the rate of backpropagation learning

Factors	Low-Level	High-Level
Learning Algorithm	LM	GDX
Number of hidden layers	1	2
Number of Neurons	10	20
Transfer Function	Tansig	Purelin
Fixed Training Parameters		
Epoch	1000	1000
Number of input Neurons	4	4
Number of Output Neurons	1	1
Hidden Layer Transfer Function	Tansig	Tansig
Learning Rate	0.001	0.01
Validation Checks	1000	1000
Gradient Descent, min Value	1e-07	1e-05

Table 9:Design and Training Parameters

5.3 Design of Experiment

After going through the steps for building ANN model, four factors were selected to be part of the experiment and each factor has two options. These options would show how they affect the neural network performance. So, to test these parameters, a design of experiment is conducted to ensure adequate and control setting for the experiment. The definition of experiment is systematic tests conducted in controlled conditions to determine the factors effecting the output of a system and to examine if a theory or hypothesis is correct. In science and technology, experiments are vital for the advancements of practices and theories. According to Montgomery (2013), most of engineering and science problems require experiments to obtain the desired results, these types of models are called empirical models. Utilizing DOE early in a process or system can have multiple advantages such as; improvement of process yield and reduce time and effort.

Factors for a process or system can be either controllable or uncontrollable. The aims of the experiment are to narrow down the influential factors and to decide where to set them so the process would acquire the desired output. Any experiment has inputs which are referred to as factors and outputs which are referred to as response variables. Factors are manipulated to study their effects on the response variables and to recognize which factors are important and which are not (Montgomery 2013)

Statistical design of experiment refers to the planning of experiment so the data are collected and analysed in objective and valid way. The data processed by the experiment must draw a meaningful conclusion to the procedure, therefore statistical analysis is the only way to make the DOE objectified. Design of experiment has two parts, the experiment design and statistical analysis. Both parts are interrelated and depend on each other to succeed (Oehlert 2000)

5.3.1 Factorial Design

One of the most common techniques for DOE and used to evaluate the interaction between factors. There are two levels for each factor, high and low levels. Factors are referred to as K So, the sample size N is equal to 2^k. The samples of the full factorial scheme are a part of the sample space where change occur one at a time.

Therefore, effect of each factor over the response variable will not be confounded with other factors. Factorial design of 2^4 is used for this research to test Artificial Neural network performance. Four factors with two levels are chosen as parameters to study their influence on modelling degradation. Table 9 shows the four factors which are learning algorithm, Number of hidden layers, Number of neurons and Transfer functions.

Since this is factorial design, two levels are selected for each factor. High and low levels for each factors. As mentioned earlier, learning algorithm factors are Levenberg-Marquardt BP (LM) for Low level and Gradient Descent BP (GDX) for high level. Hidden layers will be experimented on 1 layer and 2 layers. Number of neurons are 10 for low level and 20 neurons for high level. The last factor is the transfer function in the output layer, low level is Tansig function and high level is Purelin. The 16 combination models are demonstrated in table 10

The experiment is conducted three times to eliminate noisiness and to ensure minimum error or misreading. A total of 48 experiment conducted using MATLAB with 16 combinations replicated three times.

Model No	Factors	Model No	Factors
1	LM,L1,N10,Tansig	9	GDX,L2,N10,Purelin
2	GDX,L2,N20,PureLin	10	GDX,L2,N20,Tansig
3	GDX,L1,N10,Tansig	11	GDX,L2,N10,Tansig
4	LM,L2,N10,Tansig	12	GDX,L1,N20,Tansig
5	LM,L1,N20,Tansig	13	GDX,L1,N10,Purelin
6	LM,L1,N20,Purelin	14	LM,L1,N20,Purelin
7	LM,L2,N20,Purelin	15	LM,L2,N10,Purelin
8	GDX,L1,N20,Purelin	16	LM,L2,N20,Tansig

Table 10:ANN Models

5.3.2 ANOVA (Analysis of Variation)

It is very important to know if the results of experiments happened due to chance or not. Analysis of variance is usually performed after design of experiment to know the factors impact on the outcome, to determine if the factor is significant or insignificant, p-value should be less than 0.05. This means that any effect that is likely to occur less than 0.05 by chance is statically significant. When the effect is significant the null hypothesis (H_0) is rejected. Two way ANOVA measures the main effects of each factor and the interaction between them, therefore it is used for this research. Also, Minitab is used for conducting the ANOVA and presenting the results

For ANOVA test to be valid, certain criteria must be meet before doing the test, these are:

1. Tested data should be well distributed
2. Errors are normally distributed
3. Each case is independent

When conducting ANOVA test, several parameters are measured to test the hypothesis. Degree of freedom, sum of squares, mean square, the total degree of freedom and F-test are all attained before calculating the P-value as shown in Table 11

Source of Variation	d.f.	SS	MS	F_0
Factor A (between groups)	a-1	$SSA = \sum_{i=1}^{a} n_i \left(\bar{y}_{i.} - \bar{y}_{..}\right)^2$	$MSA = \frac{SSA}{(a-1)}$	$\frac{MSA}{MSE}$
Factor B (between groups)	b-1	$SSB = \sum_{j=1}^{b} n_j \left(\bar{y}_{.j} - \bar{y}_{..}\right)^2$	$MSB = \frac{SSB}{(b-1)}$	$\frac{MSB}{MSE}$
Error (within groups)	(a-1)(b-1)	$SSE = SST - SSA - SSB$	$MSE = \frac{SSE}{(a-1)(b-1)}$	
Total	N-1	$SST = \sum_{i=1}^{a} \sum_{j=1}^{n} \left(y_{ij} - \bar{y}_{..}\right)^2$		

Table 11:ANOVA Factors

Chapter 6: Results & Discussion

The results of feed forward neural network for estimating defects age is investigated. ANOVA is used to find out which parameters have significant effect on ANN. Also, the estimated deterioration scenarios are presented.

DOE test the parameters for Artificial neural network and examine their impact on achieving the desired target. Factorial design of ($\mathbf{2^4}$) is used on ANN design parameters with the defects age as the target. A total number of 16 ANN is designed using MATLAB, each of these scenarios was replicated for three times to limit errors or noises. The total runs were 48 and the results are evaluated using Mean Square Error (MSE), regression and error histogram. These tools measure the difference between targets (true age) and outputs (ANN age). These plots show the neural network performance after training. Moreover, ANOVA is used on mean square error for the models to test the null hypothesis. The factors would be either significant or insignificant on ANN. Furthermore, to realize the main effects importance and the interaction between them. These procedures are to obtain a valid outcome on the performance of feed forward neural network for deterioration modelling.

Learning Algorithm, Number of hidden layers, Number of hidden neurons and transfer functions are the four factors used for this research. These are very vital parameters when designing any type of neural network. FFNN is function fitting network used in this case to examine their ability to map between the input (explanatory variables) and the target (response variable). The inputs of networks are type of bridge, exposure, member type and defect type. The target is the defect age recorded while inspection. Neural networks are trained to estimate the output based on the mapping or curve fitting between the provided inputs and target

6.1 ANN Results

In this section, the sixteen models are presented with two plots to illustrate ANN performance on obtaining the defect age close to the target data. The best result for each of the 16 models are picked from the three replications and presented below. The three replications have similar results.

Exp Model	Model 1				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm :Levenberg Marquardt BP	One Hidden Layer	10 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function:Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.04368	0.03574	0.03635
Regression	0.61131	0.57168	0.55802

This model has the low level option for all of the four factors, Levenberg Marquardt Back-propagation, ten neurons, one hidden layer and Tansig for transfer function. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 14. These illustrations are performance plot, regression, and error histogram. The performance of the network is checked through the Mean Square Error which is provided in the performance plot, Figure 14a. The training stopped at Epoch 56 but the validation check stopped at epoch 8 with **0.04368** as the best validation performance. The second graph shows the regression ratio of **0.61131**, Figure 14b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, indicates a random and poor relationship. In this case, the relation is fair and mediocre, showing a degree of randomness. This regression is for all the data sets (training, validation, and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, illustrate the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is -0.1916 as provided in Appendix B. The histogram is not normally distributed.

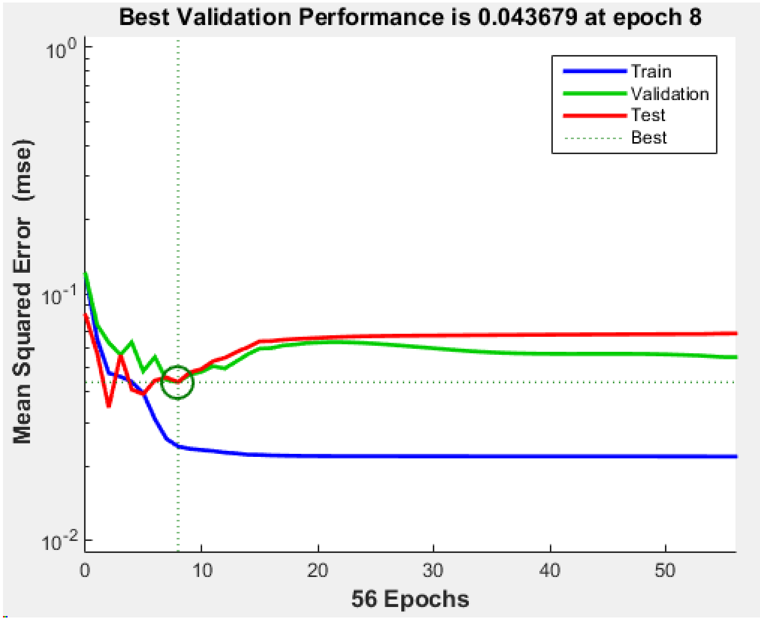


Figure 14A: MSE For Model 1

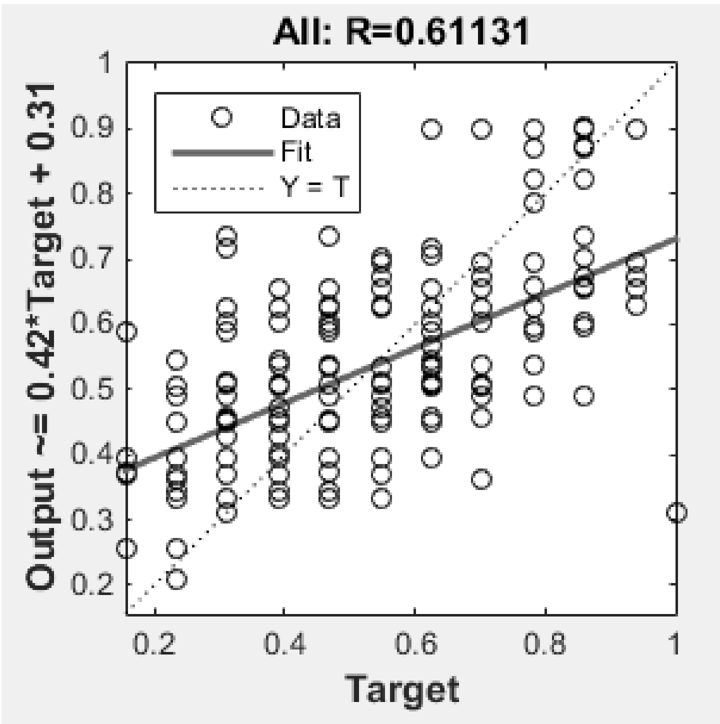


Figure 15B: Regression For Model 1

Exp Model	Model 2				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Gradient Descendent BP	Two Hidden Layer	20 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.050679	0.039701	0.041308
Regression	0.62567	0.63364	0.63294

This model has the high level option for the four factors, Gradient Descent Backpropagation, twenty neurons, two hidden layers and Purelin for transfer function. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 15. These illustrations are performance plot, regression and error histogram. The performance of the network is checked through the Mean Square Error which is provided in the performance plot, Figure 15A. The training stopped because the maximum Epoch of 1000 was reached. Unlike, the first model where the minimum gradient reached so the training was stopped. This is due the learning algorithm of GDX, it takes longer time for neural network to be trained. The validation check stopped at epoch 134 with **0.039701** as the best validation performance. The second graph shows the regression ratio of **0.63364**, Figure 15B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graphs are error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.1046** as provided in Appendix B. The histogram is not normally distributed and skewed to the left. This skewedness direction indicates the outputs are larger than the targets

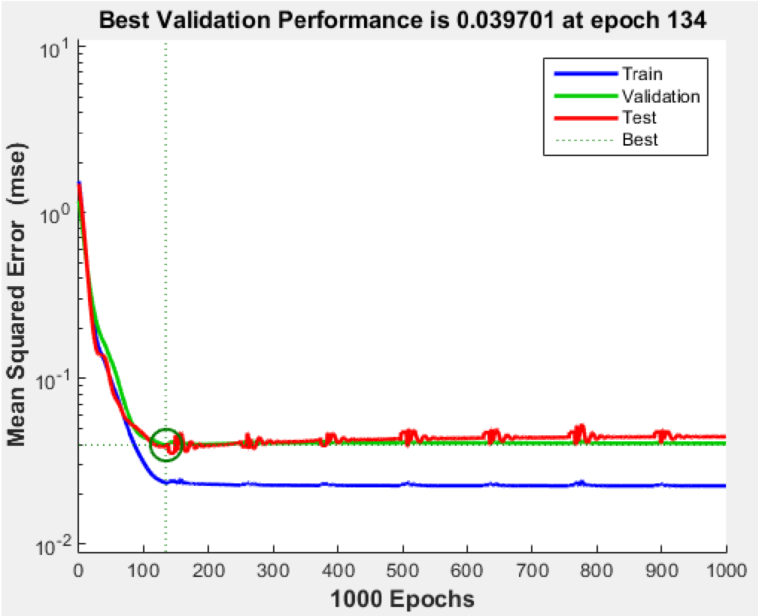


Figure 15A: MSE For Model 2

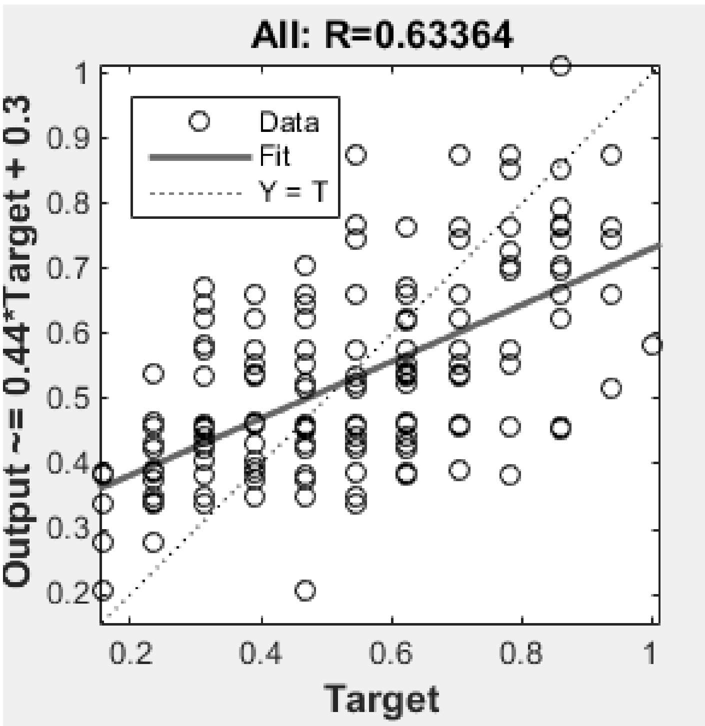


Figure 15B: Regression for Model 2

Exp Model	Model 3				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Gradient descendant BP	One Hidden Layer	10 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.034726	0.037778	0.033153
Regression	0.48094	0.46886	0.5962

This model has the high level option for the learning algorithm (GDX), the other factors are low level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 16. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 16A. Like model 2, the training was stopped due to maximum epoch was reached. The validation check stopped at epoch 189 with **0.033153** as the best validation performance. The check stops the network from overfitting, therefore once the validation error goes high, the best value is recorded. The weight and bias for the best validation value are taken as the final ones for the network. The second graph shows the regression ratio of **0.5962**, Figure 16B This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is mediocre with a value less than 60%, demonstrating a degree of randomness. Also, there are outliners values that don’t follow the line equation. This regression is for all the data sets (training, validation, and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **0.1672** as provided in Appendix B.

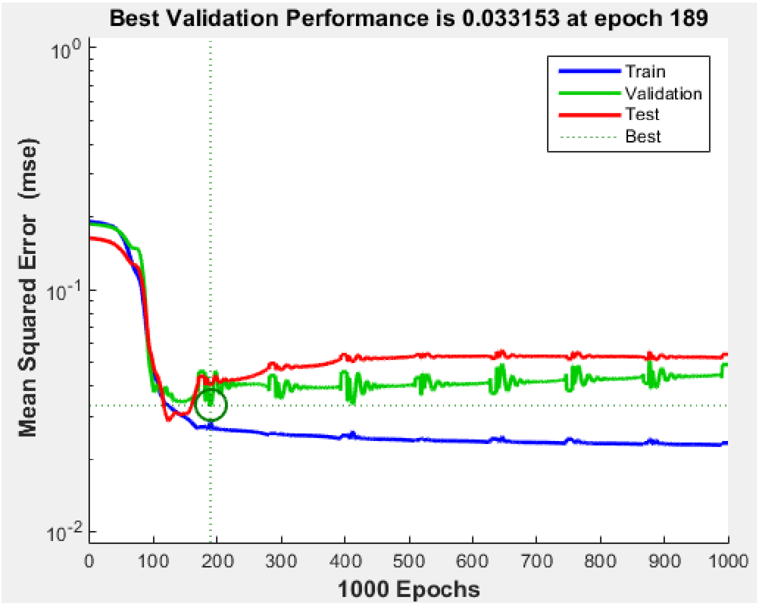


Figure 16A: MSE For Model 3

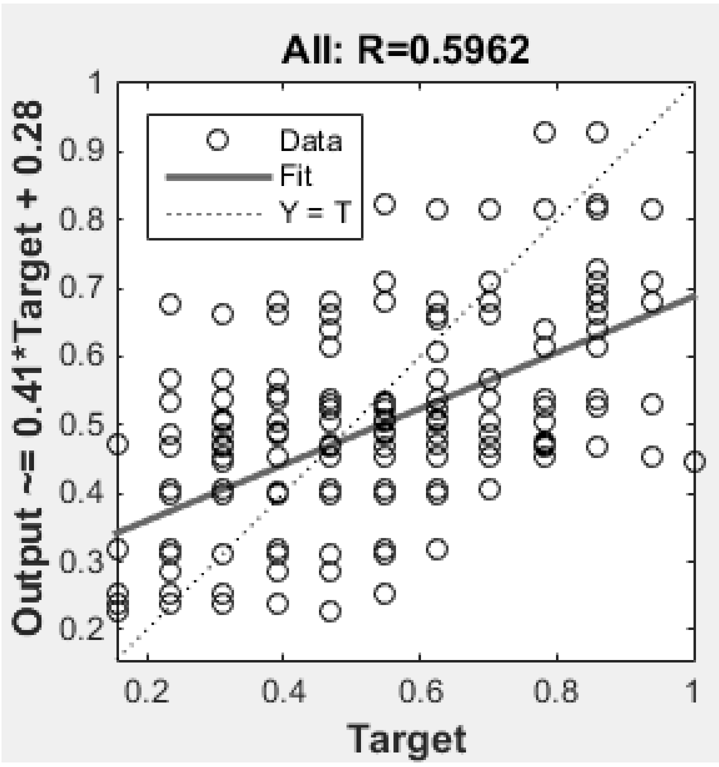


Figure 16B: Regression for Model 3

Exp Model	Model 4				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm :Levenberg Marquardt BP	Two Hidden Layer	10 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.04865	0.0264	0.030484
Regression	0.55478	0.63857	0.64011

This model has the high level option for the hidden layer only, two hidden layers are used in this treatment while the other three factors are low level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 17. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 17A. The training stopped at Epoch 55 because the minimum gradient was reached but the validation check stopped at epoch 6 with **0.030484** as the best validation performance. The learning function has stopped the network iteration to prevent overfitting. The second graph shows the regression ratio of **0.64011**, Figure 17B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation, and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.1143** as provided in Appendix B. The histogram is skewed to the left.

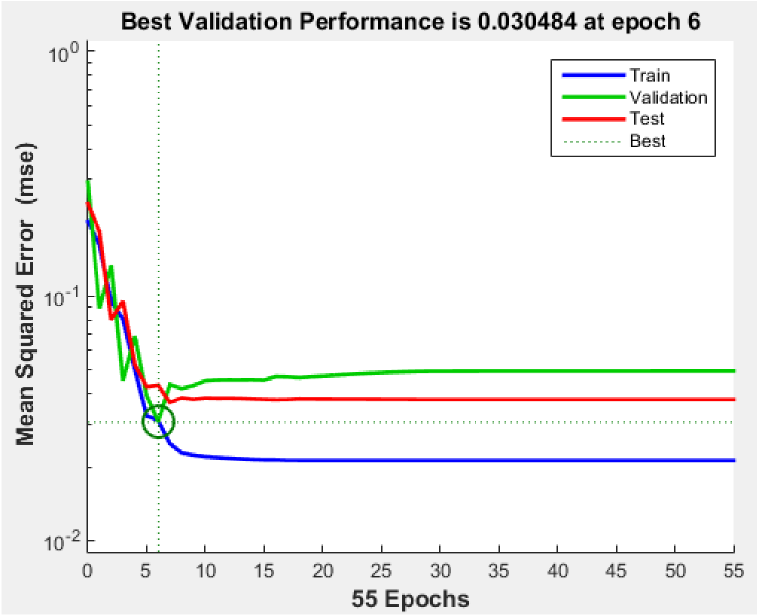


Figure 17A: MSE For Model 4

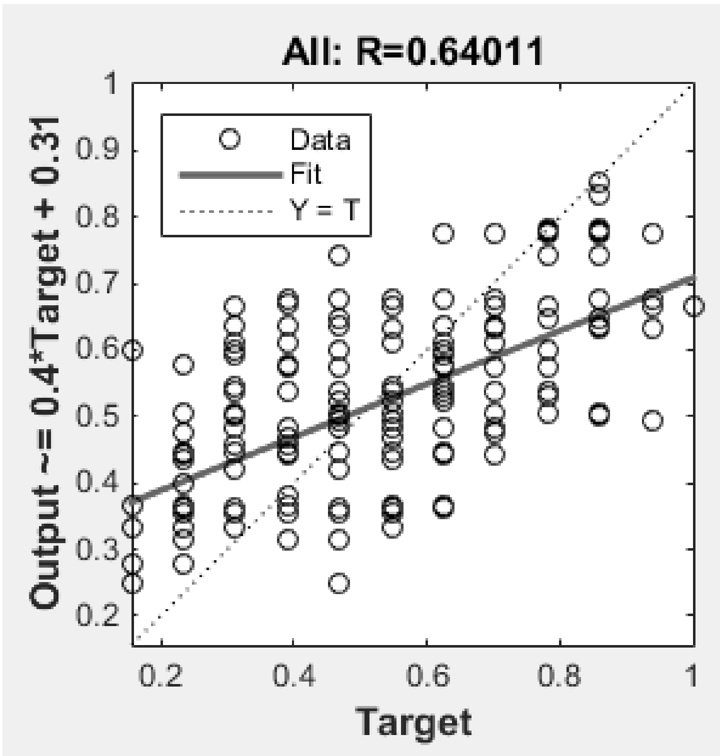


Figure 187B: Regression for Model 4

Exp Model	Model 5				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Levenberg Marquardt BP	One Hidden Layer	20 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.04443	0.038175	0.043592
Regression	0.62166	0.53779	0.64033

This model has the high level option for the hidden neurons only, twenty neurons are used in this treatment while the other three factors are low level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 18. These illustrations are performance plot, regression, and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 18a. The training stopped at Epoch 13 because the minimum gradient was reached but the validation check stopped at epoch 3 with **0.043592** as the best validation performance. The training stopped to prevent the network from overfitting and the values for weight and bias were taken in correspondence with the best validation value. The second graph shows the regression ratio of **0.64003**, Figure 18b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation, and testing). Also, there are few outliners values that do not match with line equation. Regression training set is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.06373** as provided in Appendix B

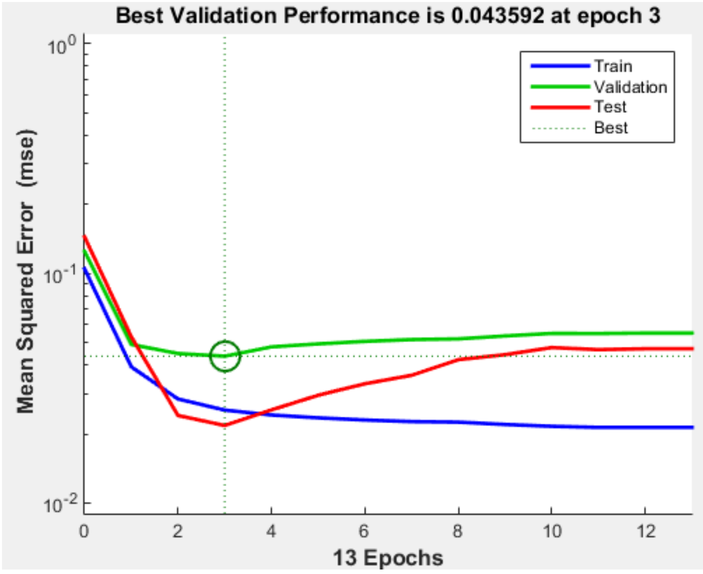


Figure 18A: MSE For Model 5

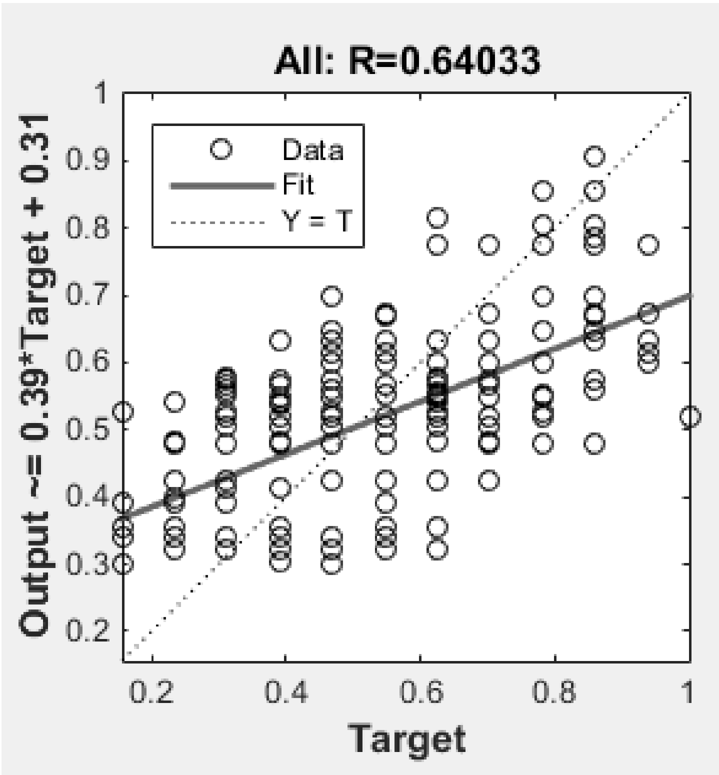


Figure 18B: Regression For Model 5

Exp Model	Model 6				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Levenberg Marquardt BP	One Hidden Layer	20 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.036214	0.021378	0.0343
Regression	0.55118	0.5911	0.50726

This model has the high level option for the transfer function for output layer, Purelin are used in this treatment while the other three factors are low level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 19. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 19A. The training stopped at Epoch 66 because the minimum gradient was reached but the validation check stopped at epoch 3 with **0.021378** as the best validation performance. The training stopped to prevent the network from overfitting and the values for weight and bias were taken in correspondence with the best validation value. The second graph shows the regression ratio of **0.5911**, Figure 19B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is mediocre, showing a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.06786** as provided in Appendix B.

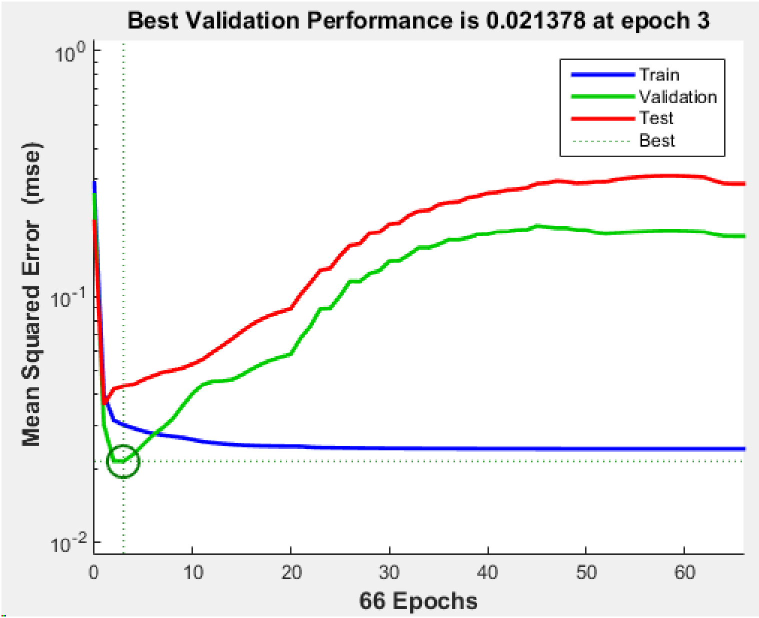


Figure 19A: MSE For Model 6

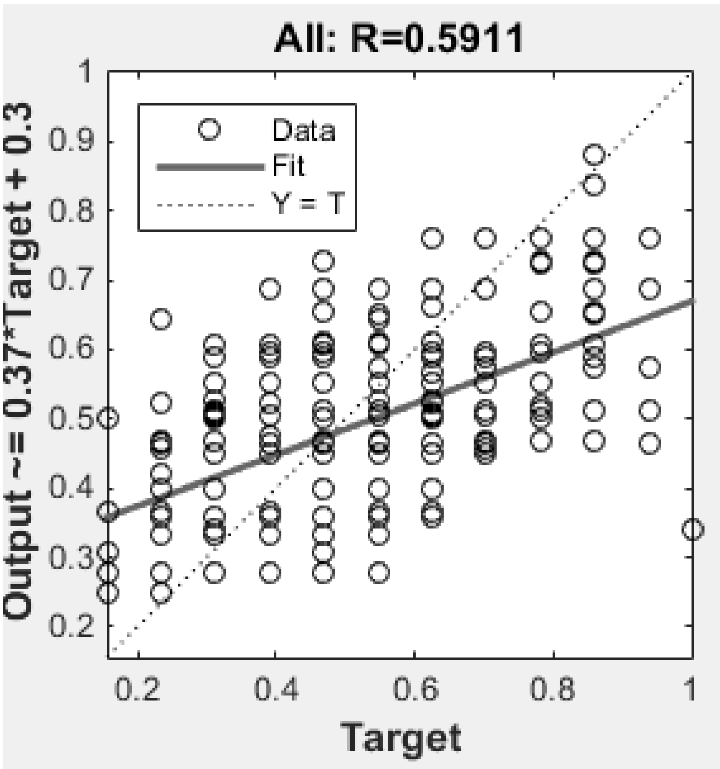


Figure 19B: Regression For Model 6

Exp Model	Model 7				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Levenberg Marquardt BP	Two Hidden Layer	20 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.047555	0.057287	0.032614
Regression	0.59675	0.57743	0.58673

This model has the low level option for the learning algorithm only, LM is used in this treatment while the other three factors are high level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 20. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, Figure 20A. The training stopped at Epoch 5 because the minimum gradient was reached but the validation check stopped at epoch 2 with **0.047555** as the best validation performance. The training stopped to prevent the network from overfitting and the values for weight and bias were taken in correspondence with the best validation value. The second graph shows the regression ratio of **0.59675**, Figure 20B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is mediocre and have a degree of randomness. This regression is for all the data sets (training, validation and testing). Also, there are outliner values that don’t fit into the line. Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.07848** as provided in Appendix B. This histogram has close frequent errors.

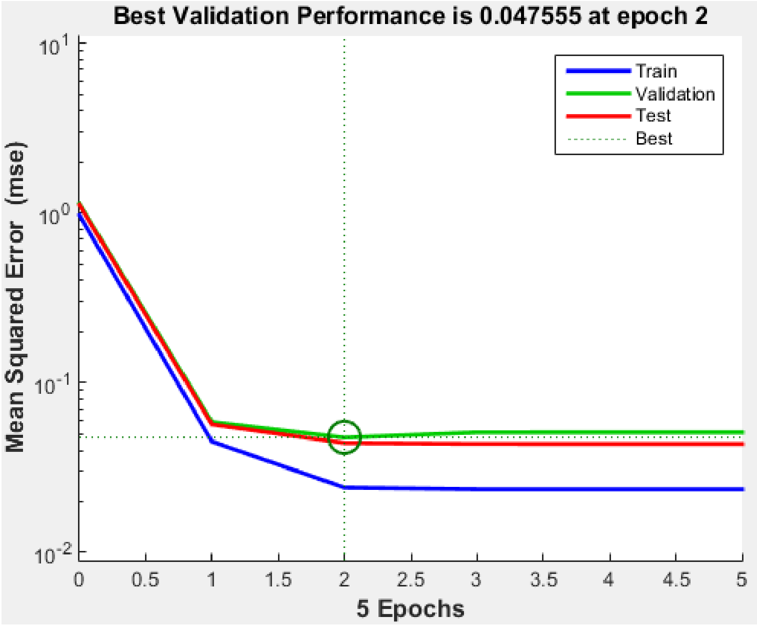


Figure 20A: MSE For Model 7

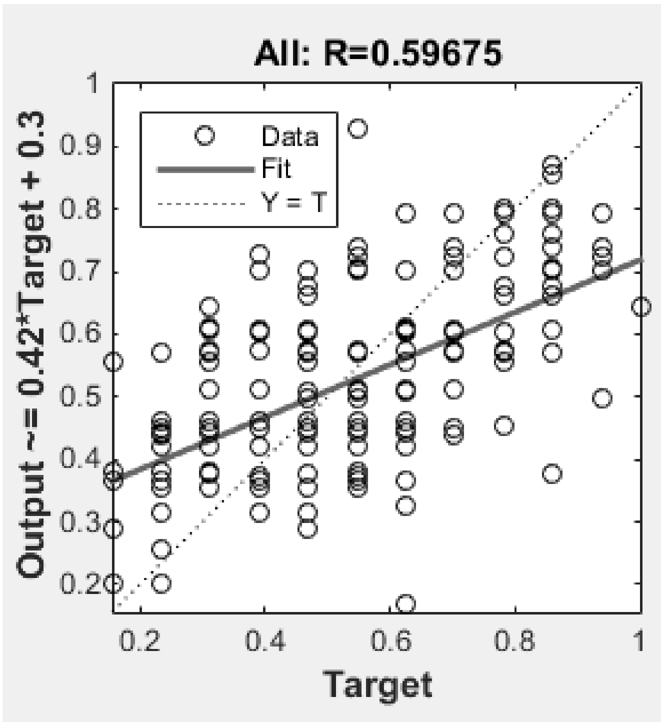


Figure 20B: Regression For Model 7

Exp Model	Model 8				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm : Gradient Descendant BP	One Hidden Layer	20 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.03367	0.03122	0.02027
Regression	0.3609	0.55816	0.62547

This model has the low level option for the hidden layer, one hidden layer is used in this treatment while the other three factors are all high-level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 21. These illustrations are performance plot, regression and error histogram. The performance of the network is checked through Mean Square Error which is provided in the performance plot, Figure 21A. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 163 with **0.020271** as the best validation performance. The validation stopped to prevent the network from overfitting and the values for weight and bias were taken in correspondence with the best validation value. The second graph shows the regression ratio of **0.62547**, Figure 21B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Outliners are also shown in the regression graph. Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **0.0515** as provided in Appendix B. The histogram is a degree of well distributed errors

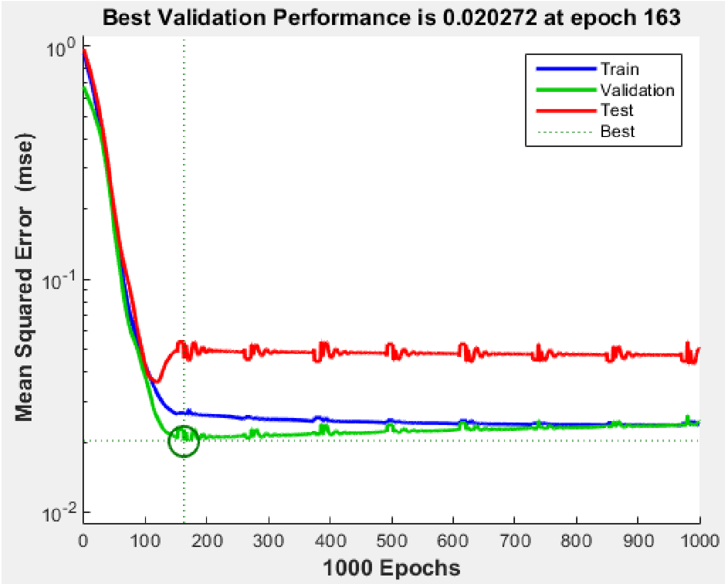


Figure 21A:MSE For Model 8

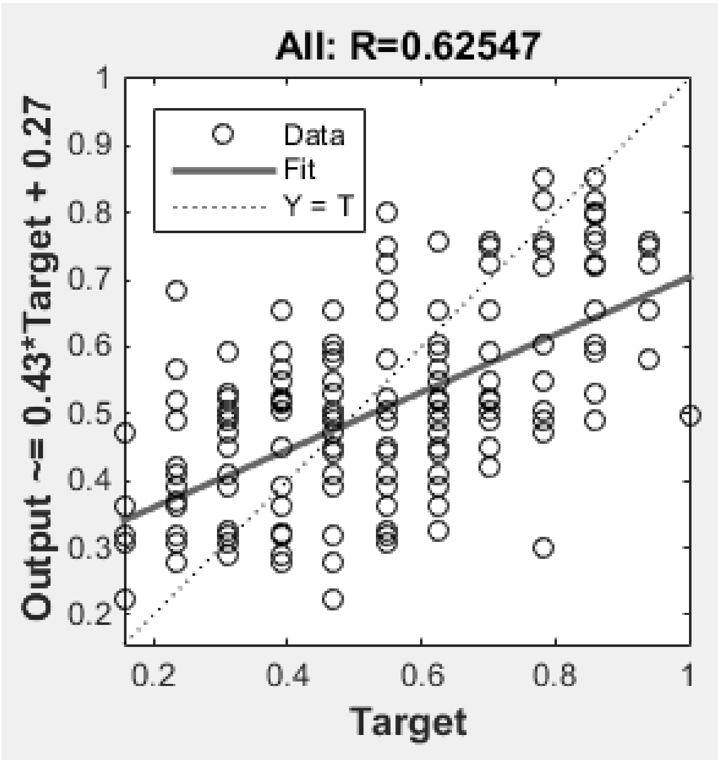


Figure 221B: Regression For Model 8

Exp Model	Model 9				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Gradient Descendent BP	Two Hidden Layer	10 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.04580	0.03362	0.03196
Regression	0.63514	0.62703	0.61191

This model has the low level option for the hidden neurons only, ten neurons are used in this treatment while the other three factors are all high-level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 22. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 22a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 909 with **0.045871** as the best validation performance. The second graph shows the regression ratio of **0.63514**, Figure 22b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **0.04671** as provided in Appendix B. The histogram has a degree of distributed errors.

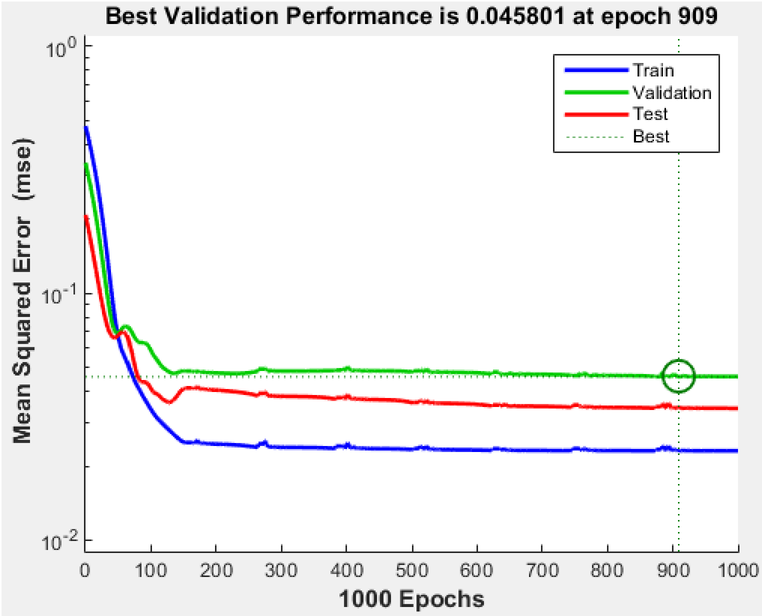


Figure 2223A: MSE For Model 9

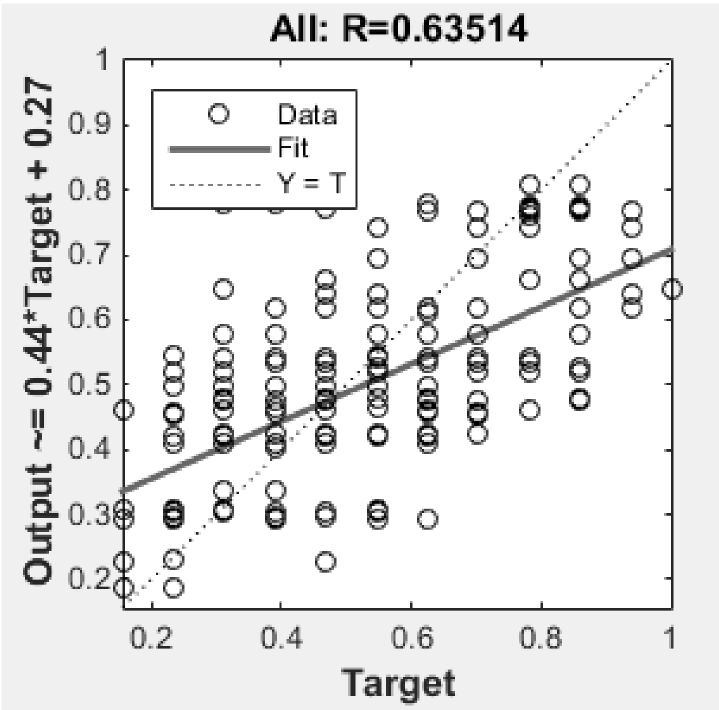


Figure 23B: Regression for Model 9

Exp Model	Model 10				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Gradient Descendent BP	Two Hidden Layer	20 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.054704	0.028655	0.03573
Regression	0.63122	0.53486	0.6197

This model has the low level option for the Transfer function only, Tansig function is used in the output layer in this treatment while the other three factors are all high-level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 23. These illustrations are performance plot, regression, and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 23a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 891 with **0.054704** as the best validation performance. The second graph shows the regression ratio of **0.63122**, Figure 23B. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Outliners are shown in regression graph where they don’t fit in the line. Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.07106** as provided in Appendix B. The histogram is a degree of well distributed errors.

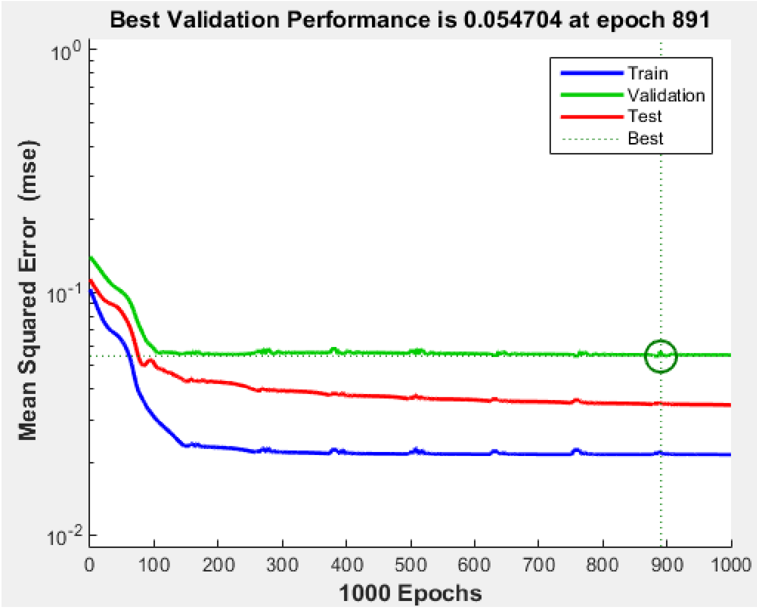


Figure 2324A: MSE For Model 10

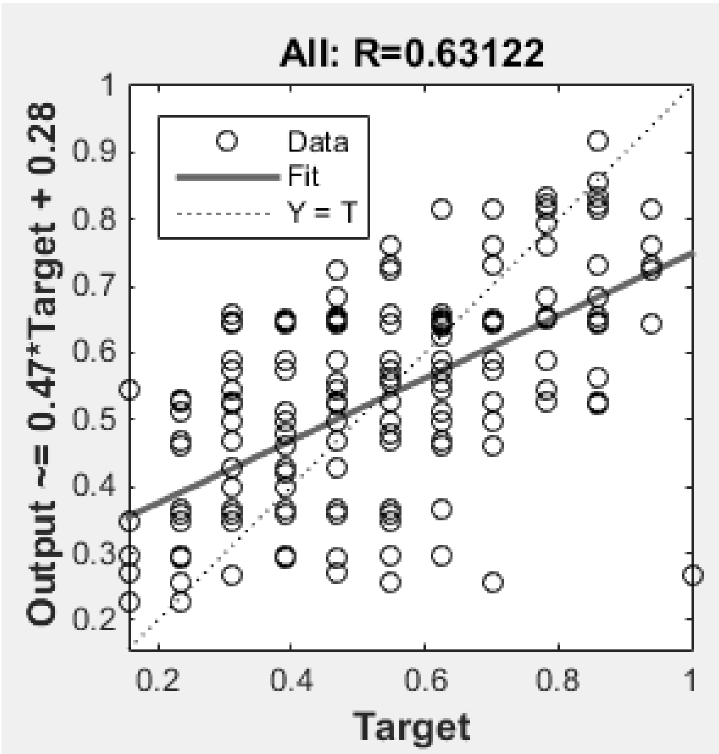


Figure 23B: Regression For Model 10

Exp Model	Model 11				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm : Gradient Descendent BP	Two Hidden Layer	10 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.01	Validation checks=1000	gd, min value =1e-05

Results	Trial 1	Trial 2	Trial 3
MSE	0.02600	0.034919	0.028012
Regression	0.64295	0.61069	0.61069

This model has the high level option for Learning algorithm and hidden layer, GDX and two hidden layer are used in this treatment while the other two factors are low-level options. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 24. These illustrations are performance plot, regression, and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 24a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 66 with **0.02600** as the best validation performance. The second graph shows the regression ratio of **0.64925**, Figure 24b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrate the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.2038** as provided in Appendix B. The histogram is skewed to the left side

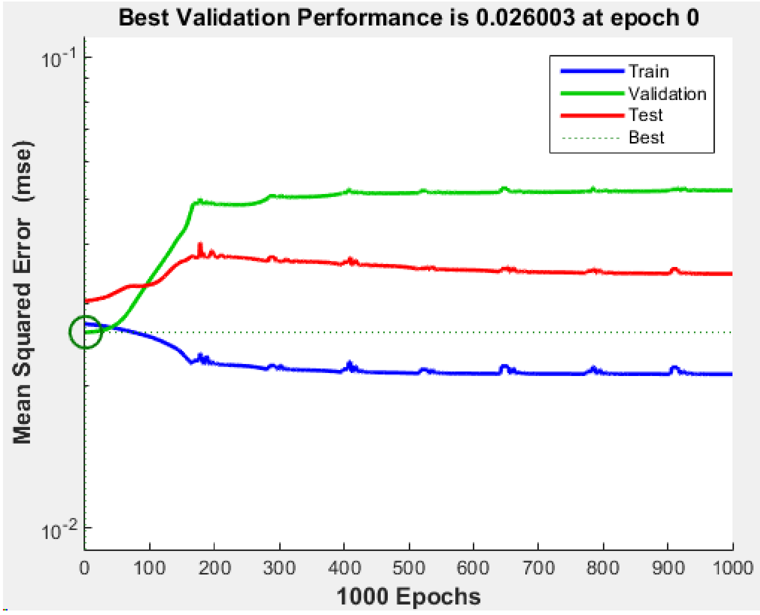


Figure 254A: MSE For Model 11

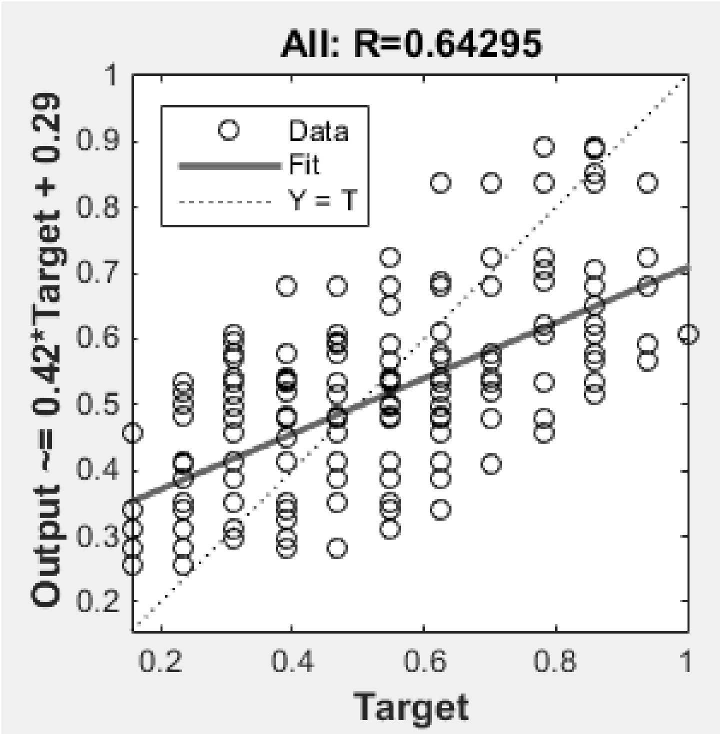


Figure 24B: Regression for Model 11

<table>
<tr><td>Exp Model</td><td colspan="5">Model 12</td></tr>
<tr><td>Input</td><td>I_1= Bridge Type</td><td>I_2= Exposure</td><td>I_3= Member</td><td colspan="2">I_4= Defects</td></tr>
<tr><td>NN Type</td><td colspan="5">Feed-Forward Neural Network</td></tr>
<tr><td>Design Parameters</td><td>Learning Algorithm: Gradient Descendent BP</td><td>One Hidden Layer</td><td>20 Hidden Neurons</td><td colspan="2">Output Transfer Function: Tansig</td></tr>
<tr><td>Fixed Training Parameters</td><td>Epoch =1000</td><td>Hidden Transfer Function: Tansig</td><td>Learning Rate=0.01</td><td>Validation checks=1000</td><td>gd, min value =1e-05</td></tr>
</table>

Results	Trial 1	Trial 2	Trial 3
MSE	0.04397	0.038801	0.043417
Regression	0.508	0.60466	0.55403

This model has the high level option for Learning algorithm and hidden neurons while hidden layer and transfer function have the low level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 25. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 25a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 157 with **0.038810** as the best validation performance. The second graph shows the regression ratio of **0.60466**, Figure 25b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.161** as provided in Appendix B. The histogram is skewed to the left side.

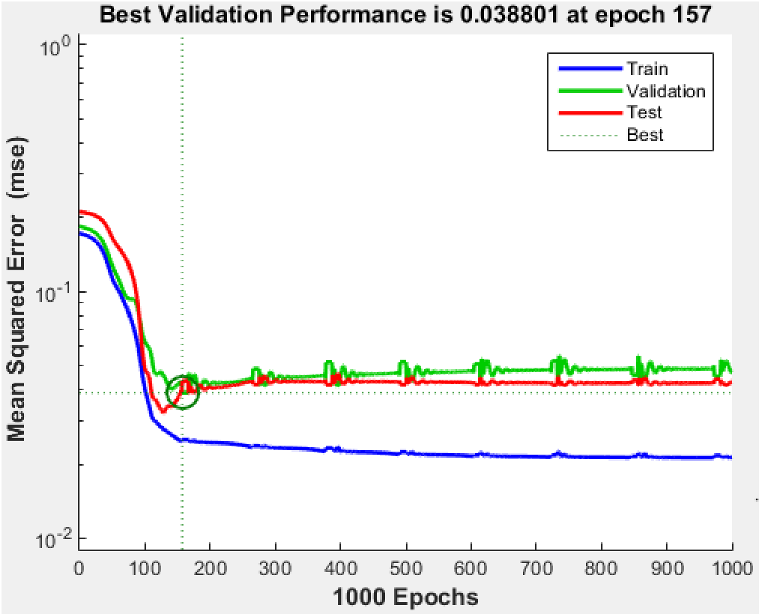


Figure 25A :MSE For Model 12

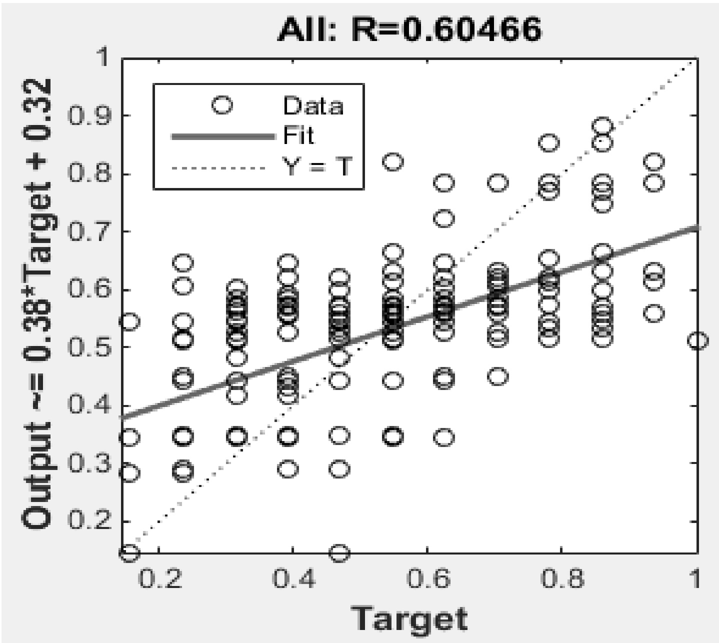


Figure 25B: Regression For Model 12

<table>
<tr><td>Exp Model</td><td colspan="5">Model 13</td></tr>
<tr><td>Input</td><td>I_1= Bridge Type</td><td>I_2= Exposure</td><td>I_3= Member</td><td colspan="2">I_4= Defects</td></tr>
<tr><td>NN Type</td><td colspan="5">Feed-Forward Neural Network</td></tr>
<tr><td>Design Parameters</td><td>Learning Algorithm: Gradient Descendent BP</td><td>One Hidden Layer</td><td>10 Hidden Neurons</td><td colspan="2">Output Transfer Function: Purelin</td></tr>
<tr><td>Fixed Training Parameters</td><td>Epoch =1000</td><td>Hidden Transfer Function: Tansig</td><td>Learning Rate=0.01</td><td>Validation checks=1000</td><td>gd, min value =1e-05</td></tr>
</table>

Results	Trial 1	Trial 2	Trial 3
MSE	0.028972	0.032622	0.026108
Regression	0.48295	0.57212	0.56008

This model has the high level option for Learning algorithm and Transfer function while hidden layers and hidden neurons have the low level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 26. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 26a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 180 with **0.032622** as the best validation performance. The second graph shows the regression ratio of **0.57212**, Figure 26b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.05924** as provided in Appendix B

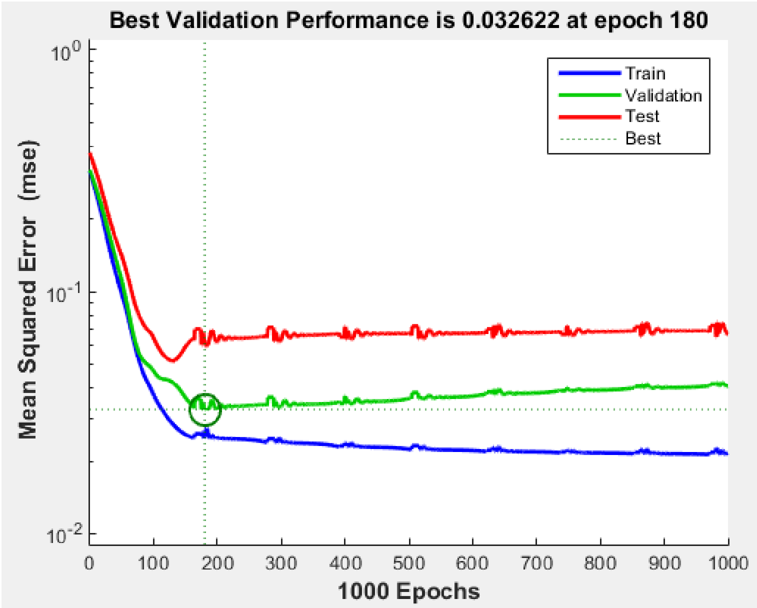


Figure 26A: MSE for Model 13

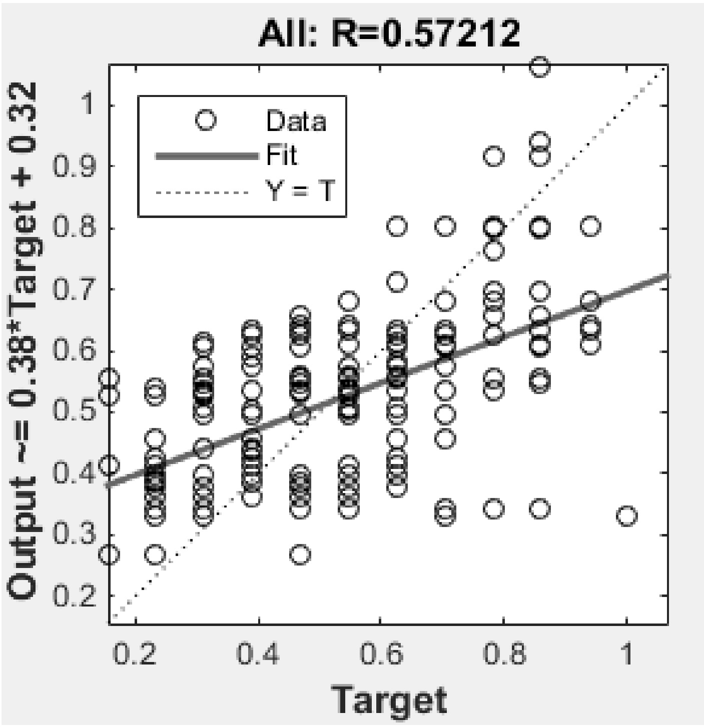


Figure 26B: Regression for Model 13

Exp Model	Model 14				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Levenberg Marquardt BP	One Hidden Layer	20 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.039796	0.035942	0.034827
Regression	0.54238	0.64477	0.52955

This model has the low level option for Learning algorithm and hidden layers while hidden neurons and transfer function have the high level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 27. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 27a. The training stopped because the maximum epoch is reached. The validation check stopped at epoch 180 with **0.035942** as the best validation performance. The second graph shows the regression ratio of **0.64477**, Figure 27b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **0.03213** as provided in Appendix B

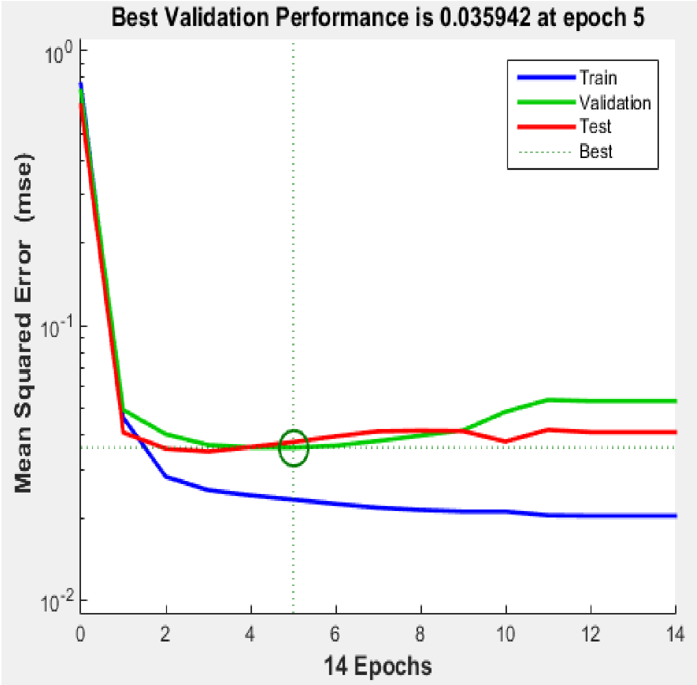


Figure 27A: MSE For Model 14

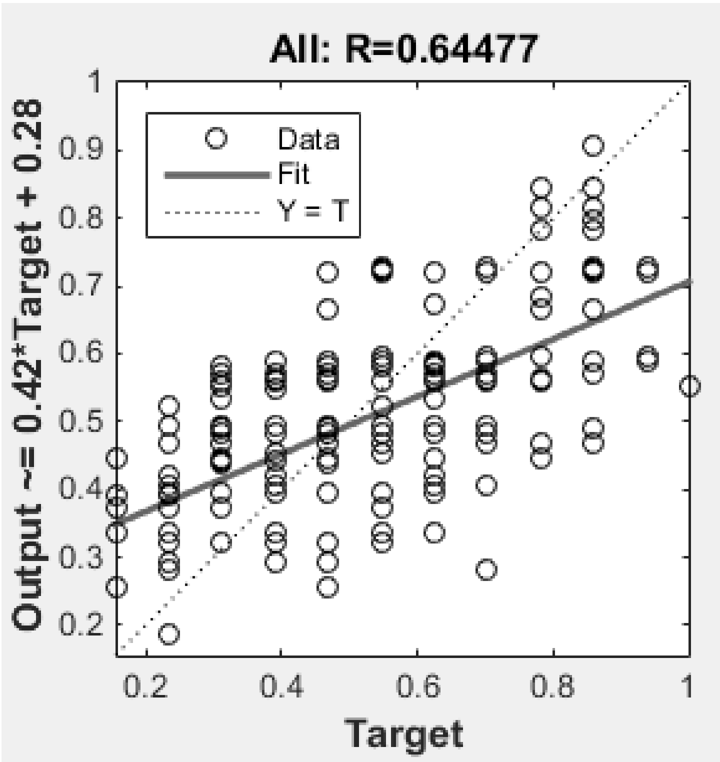


Figure 27B: Regression for Model 14

Exp Model	Model 15				
Input	I1= Bridge Type	I2= Exposure	I3= Member	I4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm: Levenberg Marquardt BP	Two Hidden Layer	10 Hidden Neurons	Output Transfer Function: Purelin	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.025295	0.036384	0.04007
Regression	0.61791	0.62607	0.58249

This model has the low level option for Learning algorithm and hidden neurons while hidden layers and transfer function have the high level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 28. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through Mean Square Error which is provided in the performance plot, figure 28a. The training stopped because the minimum gradient descent is reached at epoch 8. The validation check stopped at epoch 3 with **0.036384** as the best validation performance. The validation stopped to prevent the network from overfitting. The second graph shows the regression ratio of **0.62607**, Figure 28b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is fair and medium, demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **0.03518** as provided in Appendix B

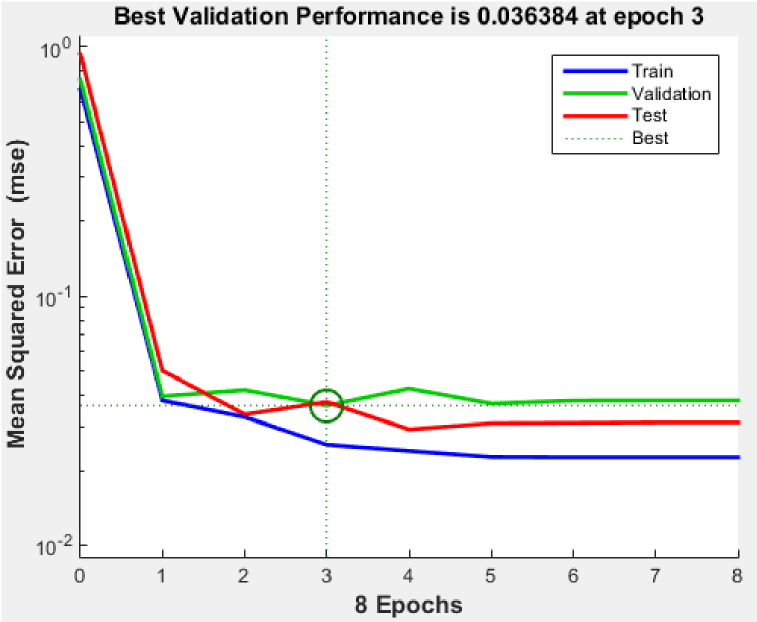


Figure 28A: MSE For Model 15

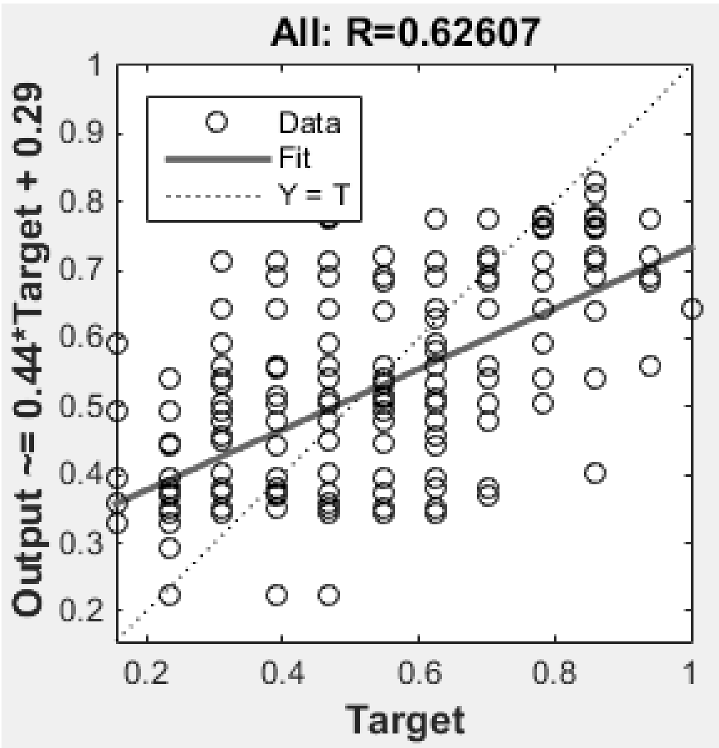


Figure 28B: Regression For Model 15

Exp Model	Model 16				
Input	I_1= Bridge Type	I_2= Exposure	I_3= Member	I_4= Defects	
NN Type	Feed-Forward Neural Network				
Design Parameters	Learning Algorithm :Levenberg Marquardt BP	Two Hidden Layer	20 Hidden Neurons	Output Transfer Function: Tansig	
Fixed Training Parameters	Epoch =1000	Hidden Transfer Function: Tansig	Learning Rate=0.001	Validation checks=1000	gd, min value =1e-07

Results	Trial 1	Trial 2	Trial 3
MSE	0.03534	0.054244	0.04872
Regression	0.57367	0.6317	0.57929

This model has the low level option for Learning algorithm and Transfer while hidden layers and hidden neurons have the high level option. Three main graphs to evaluate the results of the neural network for this model are presented in Figure 29. These illustrations are performance plot, regression and error histogram. The performance of the network is monitored through the Mean Square Error which is provided in the performance plot, figure 29a. The training stopped because the minimum gradient descent reached at epoch 7. The validation check stopped at epoch 2 with **0.054244** as the best validation performance. The second graph shows the regression ratio of **0.6317**, Figure 29b. This relationship is between the targets (actual outputs) and the neural network output. When R is close to 1, indicates a good relationship and when R is close to zero, this indicates a random and poor relationship. In this case, the relation is average and demonstrating a degree of randomness. This regression is for all the data sets (training, validation and testing). Training set regression is higher as provided in appendix B. The last graph is error histogram, it illustrates the difference between Targets and neural network outputs, the values should be close to zero. The most frequent error is **-0.02774** as provided in Appendix B.

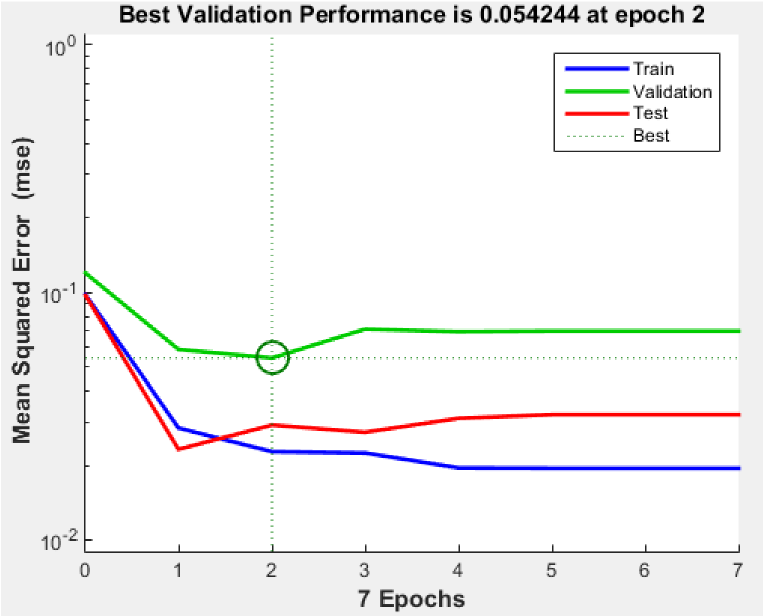


Figure 28A: MSE For Model 16

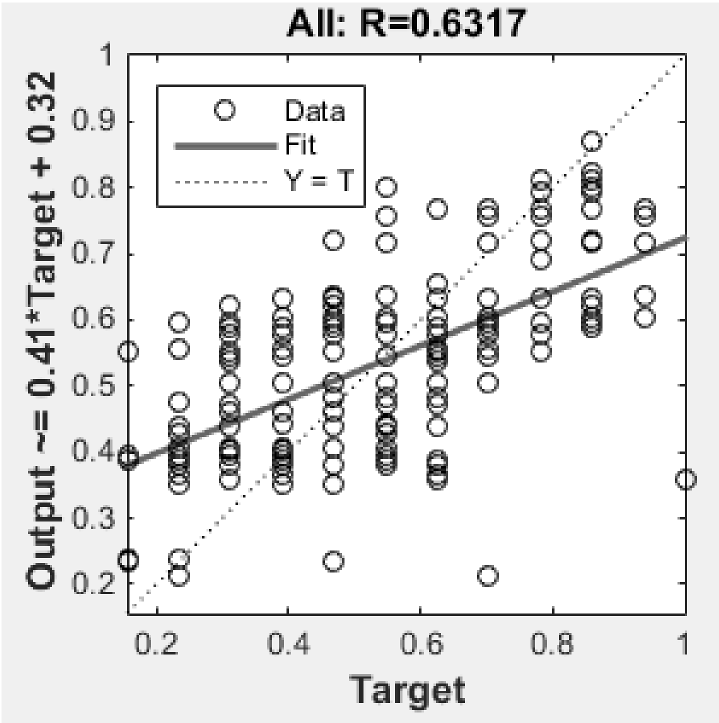


Figure 29B: Regression for Model 16

6.1.1 Summary of Results

Model No.	MSE	Regression
M1	0.04368 at Epoch 7	0.61131
M2	0.039701 at Epoch 134	0.63364
M3	0.033153 at Epoch 189	0.5962
M4	0.030484 at Epoch 6	0.64011
M5	0.043592 at Epoch 3	0.64033
M6	0.021378 at Epoch 3	0.5911
M7	0.047555 at Epoch 2	0.59675
M8	0.02027 at Epoch 163	0.62547
M9	0.0458 at Epoch 909	0.63514
M10	0.054704 at Epoch 891	0.63122
M11	0.026 at Epoch 0	0.64295
M12	0.038801 at Epoch 157	0.60466
M13	0.032622 at Epoch 180	0.57212
M14	0.035942 at Epoch 5	0.64477
M15	0.036384 at Epoch 3	0.62607
M16	0.054244 at Epoch 2	0.6317

Table 12: Summary of Models

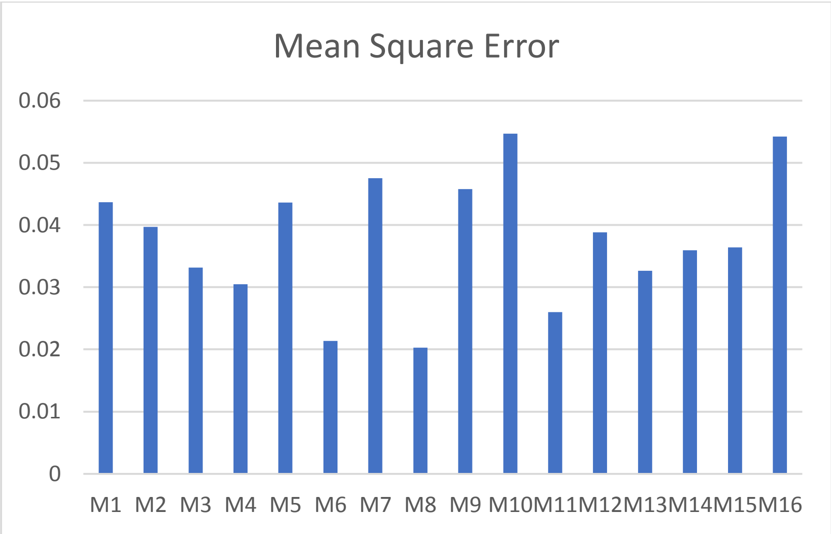


Figure 29: Histogram of MSE for 16 Models

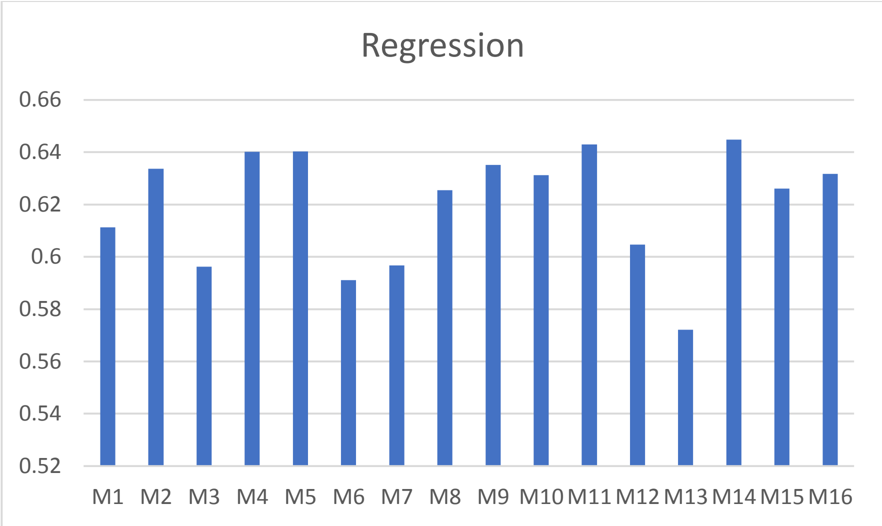


Figure 30: Histogram of Regression for 16 Models

- The best trial for each model is selected and presented in table 12. Also, MSE values for each model is presented in histogram shown above. There is difference between the MSE for the sixteen models.
- Model 8, Model 6 and Model 11 have the best mean square error values. They achieved 0.02027,0.02138 and 0.026, respectively, as shown in the above histogram. Comparing the epoch of mean square error for the models, Levenberg Marquardt BP training is faster than Gradient descent backpropagation. Although low Epoch might indicate underfitting for neural network, this is not the case here. The results illustrate low MSE value with low and high Epoch. The average value for MSE for the sixteen models is 0.0377.
- The best regression values recorded are 0.64477,0.64295 and 0.64033 for Model 14, Model 11 and Model 5, respectively. Only Model 11 has also achieved one of the best value for MSE. This indicates that regression and MSE values might not be parallel to each other all the time. The best trials are selected based on the regression values, thus, the best trials might not have the best values of MSE. Nevertheless, regression and mean square error values always provide a compatible and close indication of the network performance.

- All the models with GDX as learning algorithm have a high Epoch, except Model 11 with Epoch of zero. This model has two hidden layers with ten neurons in each and Tansig as output transfer function. The training stopped when 1000 Epoch is reached which is the maximum value. The best validation performance is at Epoch zero and this might indicate overfitting. Also, all GDX networks didn't reach the minimum gradient of 1e-05, the training took time and stopped at the maximum Epoch.

6.1.2 Discussion

- Levenberg Marqaudt Backpropagation learning algorithm has a higher rate for training ANN. It is very fast training function where the minimum gradient is reached with low Epoch value. Whereas, Gradient descent backpropagation has low speed in training the neural network, the maximum Epoch is reached in all the models. This finding confirms the previous knowledge about the two functions as mentioned earlier in literature review chapter 3. Mathworks experiment on the two-training algorithm is valid and it can work on different scenarios. In this research, training algorithm is one of the four design parameters and in each model it had different combination, nevertheless, it had showed the exact same result, validating the earlier assumption.
- Feed-forward neural network is approximation function which creates link between target and inputs. In this experiment, the highest percentage of regression of all the models doesn't exceed 65% which means 35% of the output doesn't match target. Despite having different design parameters, most of the models showed close results. This finding goes along with the definition of FFNN and with the other scholars' research which mentioned the robust aspect of estimating the outcome but is weak in predicting and coming up with new data. The type of data has direct impact on the performance of feed forward neural network and this proven by results. Part of the inserted data for this experiment is scattered and has a degree of randomness.
- Most of the sixteen models provided similar results on the same inserted data due to the controllable experiment. Building neural network to estimate or predict bridge deterioration is complicated, therefore design of experiment had facilitated the design. However, there are no previous research or literature

review on the design of experiment for neural network for deterioration prediction to compare the performance of DOE.

- The results for all neural networks model, show randomness and unmatched outputs with targets. The mean square error for the network models range between 0.02 to 0.05. While the values show good outcome, MSE should been lower since the targets value were provided in a scale of 0-1. If the results were accurate, MSE would be lower. Regression provide the actual relationship between the outputs (ANN age) and targets (true age), the highest regression result for all the models don't exceed 65%. This mean a 65 percent match between the outputs and targets, the results are not considered poor or unsatisfying but rather fair results with random values. The inaccurate and random values is the outcome of the feedforward neural network mapping . Another measurement for the neural network performance is error histogram, all histograms show errors more than zero, confirming the inaccuracy of the outputs.

6.2 ANOVA

The analysis of variance was performed on the results of the 16 models for a better understanding of the factors impact on neural networks performance. In this case, two-way ANOVA is used to check the main effects factors and the interaction factors. Before ANOVA was conducted the three main criteria mentioned in chapter 5 are met.

a. Main Effects

After running analysis of variance on the mean square error for 48 experiments, hidden neuron is a significant factor with p-value $0.002<0.05$. According to the main effect plot, figure 6.17, ten neurons is better for ANN outcome than twenty neurons. The significance of the factor means there is a difference between ten neurons MSE and twenty neurons MSE. The mean square error for 10 H-Neurons is 0.034 while twenty neurons have higher MSE of 0.0405.

The other factors did not achieve p-value<0.05, as provided in appendix B. This means that two levels; low and high for learning algorithm, hidden layer and transfer function have the similar impact on ANN performance, Hence the difference between the effects of the two options is insignificant.

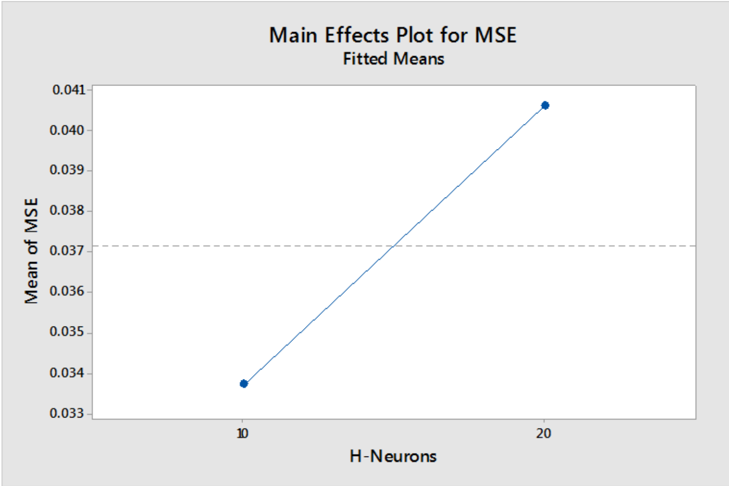


Figure 31:Main Effect Plot for Hidden Neurons

b. Interaction Factors

Two-way ANOVA provide the analysis of factor interaction to test if the interaction between main effects have significant impact on mean square error for the sixteen ANN models. The only interaction with P-value>0.05 is Hidden neurons*Transfer function with p-value of 0.015. This leads to rejection of null hypothesis(H_0). Figure 6.18, illustrate the interaction between hidden layer and transfer function. When the function is Purelin it works better with one hidden layer achieving average of 0.032 MSE while with two hidden layers the MSE goes higher to 0.038. On the other hand, Tansig works slightly better with two hidden layers than one hidden layer. The other Interaction are presented in Appendix B.

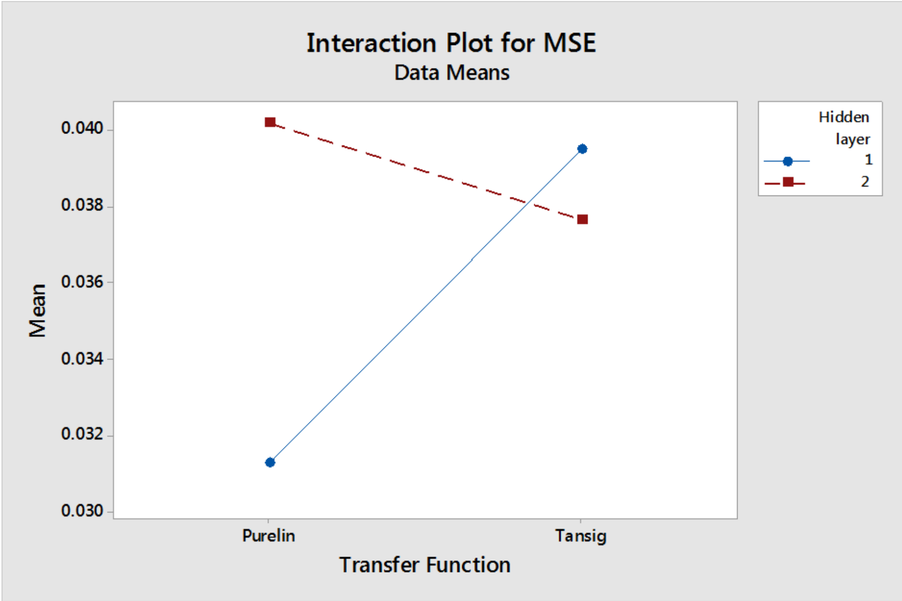


Figure 32: Interaction Plot between Hidden Layer and Transfer Function

Discussion

- ANOVA outcomes provide another insight on the influence of the design parameters on Artificial Neural network. When the factor is not significant, it means the two options has similar impact on mean square error results. In this research, there are three factors that came as insignificant, Learning algorithm, Hidden layer and Transfer function.
- Levenberg Marquardt and Gradient descent are two backpropagation learning technique and their similar impact on MSE values indicates similar training method. Nevertheless, one is faster than the other as mentioned in the earlier section. This research finding is very important and unique since there is no previous literature review on the matter. This insight could be a valid through all the cases or only true for this experiment. Hidden layer is also found as insignificant factor which means that one and two hidden layers had the same impact on MSE. Two hidden layers are usually associated with overfitting if the network is small, but in this case the results are similar with one hidden layer. This finding is true for this experiment but the previous knowledge indicates that the two hidden layers have different impact on the results. This indicates other factors such as Feed forward network and type of data might have caused this finding. Output Transfer function is to refine the output values, and in this experiment using Linear and Hyperbolic Tangent Sigmoid has similar impact on mean square error for this experiment. Linear function

has better impact on the results and its supposedly is a part of universal approximation function of neural network. However, it had similar impact with sigmoid function on the output.

- Hidden Neurons is the only significant factor where ten neurons have better impact on the results than twenty neurons. Determining the suitable number of hidden neurons is a matter of trial and error. As mentioned in methodology section, each case has its own adequate number of neurons, therefore there are no standard or rules that the findings can be compared to at this stage.

6.3 Deterioration Scenarios

After evaluating the performance of neural networks for estimating the deterioration age for RC bridges by using MSE and Regression, presenting the ANN defects age based on deterioration scenarios in graphics and tables is very important. This type of demonstrating would provide a real comparison between the true defects age and the estimated defects age. This would provide a direct insight of output of ANN as versus the target. The presentation scenarios are similar to chapter 4 presentations. Since there are 16 neural networks models, the best model in terms of regression was chosen for degradation presentation. Model 14 is selected since it has the best regression rate of 0.64477, the output(age) is taken and analysed. The average of each defect is used in presenting the deterioration

i. Defects age Versus Bridge Type

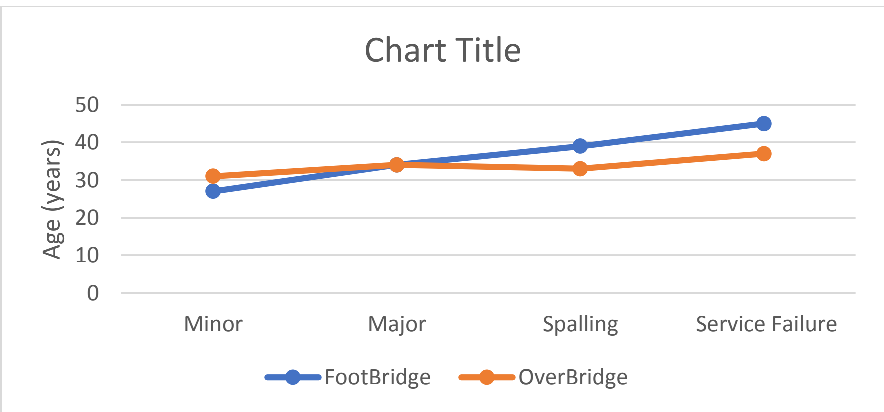


Figure 33:Footbridge Vs Overbridge

Bridge type has impact on the life cycle of the structure, footbridge and overbridge are very different type of bridges since one is for pedestrian and the other for vehicles. It is expected that overbridge would have a faster deterioration rate, this is demonstrated in figure 34 Footbridge service life is more than overbridge, only in minor defect where footbridge has an average of 27 years and overbridge has an average of 31 years. Both bridges have an equal average of 34 years for major defects. For Spalling and service failure age, footbridge has higher score of 39 and 45, respectively. While overbridge has 33 years and 37 years for spalling and service failure. The graph for footbridge is proportional while the overbridge is not, because at spalling defect, the age decrease.

ii. Defects Age Versus Bridge and Member Type

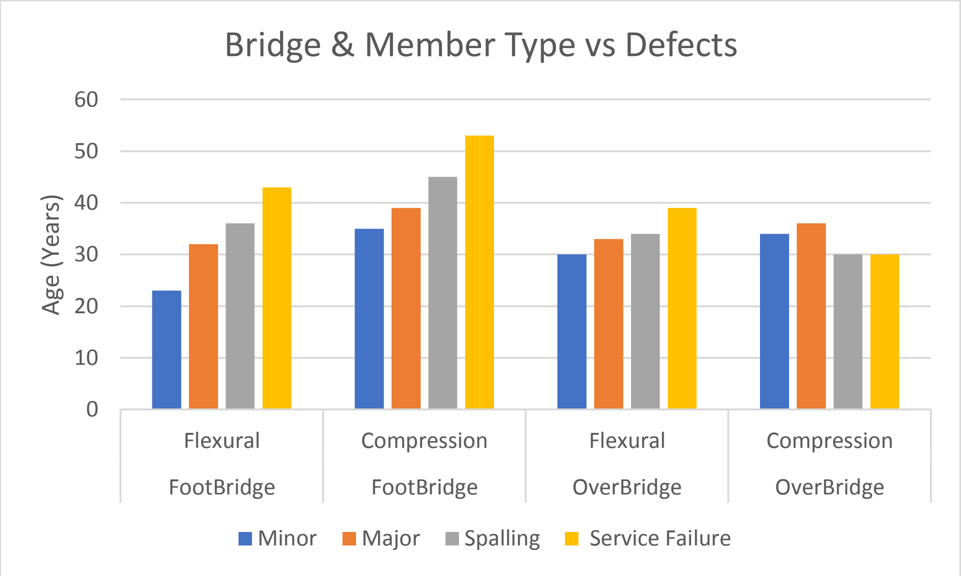


Figure 34:Bridge and Member Type

Most of the structures are split between flexural members and compression members. Figure 6.20 shows the deterioration age for bridge and member type. Compression members for footbridge has higher service life. For all the four defects, compression members deteriorate slower than the flexural members. On the other hand, overbridge does not follow the same conclusion. Flexural members in overbridge has a higher age for spalling and service failure with 34 and 39, respectively. But for minor and major defects, the compression members have the higher age with 34 and 36.

iii. Defects Age Versus Bridge Type & Exposure

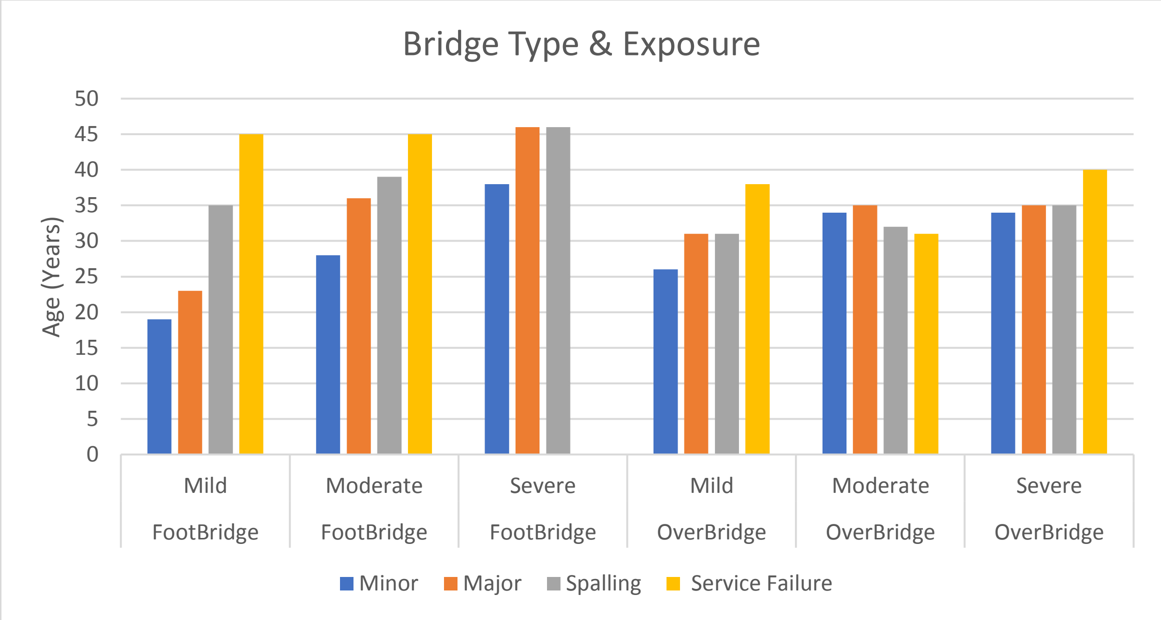


Figure 35: Bridge Type Exposure

The last factor to model against the defects is the exposure conditions. Three types of exposures available were mild, moderate and severe environment. Footbridge deterioration based on exposure are all directly proportional. Severe environment has the higher age for all the defects, excluding the service failure which is not provided in the original database. Then the moderate condition follows in the deterioration defects, the average service failure is 45 years while the minor defects is around 27 years. Mild conditions have the least life cycle, which is not expected but this result reflect the database. Both of mild and moderate service failure is expected to occur around 45 years old. Overbridge as mentioned earlier does not have a direct proportion with time (age). Severe conditions have also the lowest deterioration rate for all the four defects. Moderate condition has a higher degradation time for minor, major and spalling defects, but service failure for mild 38 years while moderate is 31 years.

iv. Four Parameters Comparisons

- **Footbridge**

Combining the four parameters scenarios for deterioration age, Service failure age for severe condition for both members is not available as mentioned in chapter 4. Major defect occur age for compression member exposed to severe environment is

54 years therefore, this scenario has the lowest deterioration rate. For most of the conditions, compression members have a better degradation resistance than flexural members.

Exposure	Member	Minor	Major	Spalling	Service Failure
Mild	Flexural	19	24	36	47
Moderate	Flexural	22	33	35	36
Severe	Flexural	34	44	43	-
Mild	Compression	17	20	31	41
Moderate	Compression	38	44	48	53
Severe	Compression	46	54	51	-

Table 13: Footbridge Deterioration Scenarios

- **Overbridge**

The service failure scenarios for sever condition and compression members are not available as mentioned in chapter 4. The defects age for severe environment with compression members follows the right deterioration patterns, it has the highest deterioration rate. Moderate exposure for compression members has the lowest deterioration rate. For flexural members, the severe conditions have the lowest deterioration rate which is opposite to the deterioration expectation

Exposure	Member	Minor	Major	Spalling	Service Failure
Mild	Flexural	27	24	34	38
Moderate	Flexural	27	33	32	38
Severe	Flexural	37	44	40	45
Mild	Compression	23	26	23	-
Moderate	Compression	43	45	31	-
Severe	Compression	29	33	32	-

Table 14: Overbridge Deterioration Scenarios

Deterioration scenarios that have a significant difference between the estimated defects age and the original age have few numbers of repetitions. This means that small number of combination for deterioration scenarios have direct effects on the results. When the number of scenario combinations increases, the results become better and close to the original deterioration age. This finding proves that ANN performance improves upon the repetition of data for training. Condition State 4 with severe exposure have the least available records, therefore their results were the weakest. Furthermore, scenarios with significant standard deviation which means a big degree of randomness have also big difference between target and output. This another proof that type of the data influence feed-forward neural network results.

Chapter 7: Conclusion

RC bridge deterioration is critical issue for civil engineering. Unlike the design process of a bridge where variables are calculated and safety factor is considered, estimating the service life of bridge is stochastic process. There are no codes or guidelines that can give an accurate maintenance time or a real-life cycle of a bridge. There are known and unknown variables that change with time. Hundreds of studies and research on the subject were published and it is still a haunting topic for scholars in structural engineering. Nevertheless, two common methods for estimating the deterioration process have dominated the area and have been used by many engineers These methods are the deterministic and Probabilistic modelling. Deterministic method uses formulas and factors to obtain the estimated service life of bridge. Although the factors used are based on records and references, they fell short to measure up with stochastic aspect of deterioration. Also, this method development is hindered because many studies have focused on the probabilistic method instead. The probabilistic method uses probability matrix to estimate the service life of the bridge. Many studies went into this field and many procedures were developed to achieve satisfactory results. Marko chain process is the most famous probabilistic method; However; it fell short to include many factors for deterioration and its more about chances and assumptions. In the last century, computers and technology revolution has solved many problems and fast-forwarded solutions in many disciplines. Artificial Intelligence is the new research topic in deterioration and service life prediction for structures. This field has gained popularity due to its huge interdisciplinary aspect. There are many A.I techniques that are used for deterioration estimate, but artificial neural network is the most growing topic in deterioration modelling.

Neural networks background is derived from human brain neurons where chains of neurons are connected to solve complex issues. ANN is broad field with limitless progress; However; there are common components for any type of NN. Every network consists of input , hidden layer and output. These layers are connected through artificial neurons and these neurons changes with estimated weights and bias. The learning process of ANN comes from the alteration of weights and bias to achieve the best results. Two types of neural networks are mainly used for deterioration estimate, Feed forward Neural Network and Recurrent Neural Network. FFNN neurons move forward in one direction and unlike recurrent network where the neurons are feedback in the hidden layers from the output layer. Feedforward Neural Net are approximation function and was selected for this research to estimate the deterioration age for RC bridge.

A database of 400 bridges located in London, UK which were constructed between 1880s to 1930s is used to train the neural network. The data had gone under extensive analysis to eliminate and filter random values. Afterwards, four main parameters are picked to serve as input for NN, bridge type, member type, exposure condition and defect type. The defect age is ANN target, footbridge and overbridge are the two-bridge type, flexural and compression members is only two-member category. Environmental exposure conditions were divided into three sections; mild , moderate and severe. The last deterioration parameter is defects group which is divided into, Minor cracking , major cracking , spalling and service failure. An approximate of forty-three combinations is fed to the neural networks. The inserted data is not homogenous, the deterioration scenarios don't have the same repetition number.

7.1 Conclusion of Results

Design of experiment is used to measure the performance of ANN in organized and systematic way. So, factorial design of 2^4 is selected and each factor has low and high level. The factors are learning algorithm, Hidden Layers, Hidden Neurons, and Transfer Function. Learning algorithm has Levenberg Marquadt BP for low level and Gradient Descent for high level. Hidden layers low level is one hidden layer while the high level has two hidden layers. Hidden neurons are 10 neurons for low level and 20 neurons for high level. The output layer transfer function for low level is hyperbolic tangent sigmoid function and linear function for high level. Sixteen neural network models are designed based on the factors combinations and each model is processed three times to minimize errors. After running the experiment, Analysis of variance is used to determine the significance of the factors

The neural network results reveal the difference between the original data for deterioration age and the neural network generated deterioration age. Although the difference varied between the sixteen models, most of the models had similar range in the similarity and differences. Three validation methods are taken to measure the performance of ANN, Mean Square Error, Regression, and Error histogram. MSE values ranging between 0.02-0.05 and Levenberg Marquadt training function has faster learning rate than Gradient descent. The performance figure shows that training, validation, and testing sets converge at the early Epoch and then start to diverge at the end, insinuating overfitting for the network , but the learning function stop the network from overfitting and record the results. Regression analysis is at best 65% which shows good results but with random values between the targets and outputs. The components of neural networks are not responsible of the random values, increasing the number of hidden layers or neurons could result in generalization of the output. The inconsistency and the randomness of the original data caused the mediocre results. The last measurement of the outcome is error histogram, the difference between the targets and outputs of ANN. The histograms have errors distributed and larger than the smallest error which means there is a difference between targets and outputs value. The form of feedforward neural network used in this research is considered the universal approximation function, however, the random data has limited the ability of ANN to map between inputs and targets, thus affecting the capability for fitting. Around thirty percent of the data is inaccurate and scattered, the random information could not have been filtered in the data analysis.

One of the major elements for neural network training and testing is the data itself. For this research, the data was collected from Bridges located in London ,UK with 50 years span. Although analysis was performed on the data to filter and eliminate as much as possible of random and inaccurate records, the data inserted to the MATLAB are still scattered and random. Moreover, the input factors are nominal whereas the target is numerical, this has created number of same input combination with very different responses. Moreover, the data isn't homogenous because each scenario combination of input has different number of replications. Furthermore, missing, and incomplete data for some of the inspected bridges had caused interrupted records which affected ANN learning ability. As a result, neural network didn't establish a good fitting function for this type of data.

Feedforward neural network is function fitting process where the network tries to establish a connection between the inputs and the targets. FFNN learning is direct process to map the data with the desired output. Since, the design process for neural network did not allow a room for generalization of the data, the outcome of 65% regression reflects that FFNN could not establish enough links with all the input and targets for excellent fitting curve. Hence, the random attribute of the data had caused FFNN mediocre performance. Therefore, other more advanced type of neural networks could have improved the results, Dynamic time series, Narx. Also, generating the missing historical records by Back propagation techniques could have improved the data, thus improving the ANN performance.

ANOVA, the analysis of variance, was performed using MSE for the 16 models. One factor had p-value <0.05 which means it has significant impact. Number of neurons is the only factor that has significant effect on the networks. This means the null hypothesis H_0 is rejected and there is a difference between MSE of the variable factor. The performance of ten neurons is better than twenty neurons. The other three factors have insignificant main effect on neural networks. This mean the low and high levels of the factors had similar impact on the performance of neural network. Also, the factor interaction analysis has shown that hidden layers and transfer function interaction is significant. No other factor interaction was detected to have significant impact on the results.

The output of neural network, the estimated defects age , was analysed based on the deterioration scenarios. In general, the footbridge scenarios had lower deterioration rate than overbridge. Also, the flexural members have higher deterioration rate than compression members. For environmental exposure, severe condition had the lowest deterioration rate which is like the original data results. This is a good indication that the original data is inconsistent and inaccurate. In deterioration scenarios wise, the estimated defects age is the almost the same as the original age. FFNN, had succeeded in fitting the data to some extent.

7.2 Limitations

The conclusion drawn from this research has limitations. ANN deterioration model cannot be generalized for all the other deterioration case, due to the followings: -

- The time and location of the collected data for bridges. Although the data covered bridges within 50 years span, this is not enough since a lot of the data were refined. Also, the location is restricted to England. So, it cannot be generalized for other locations.

- The results of variable factor are relevant for this case only. Whether the factor is significant or insignificant, this can change when the model changes, thus this is relevant for this model
- The levels of each factor, low and high can change when the options of the factor differ. Significant or insignificant for factor changes with the options of the level. If one of the level option changes, then the factor result might differ from significant to insignificant or vice versa
- Studying only four defects ,two bridges, two members and three exposure conditions is very limited information for estimating a bridge deterioration age. The input parameters are few and including more parameters such as the number of spans, the repair records and concrete mix materials can improve the results

7.3 Future Work

The aim for this study is explore the use of artificial neuron network for predicting the deterioration age for reinforced concrete bridges. Future work can include service life or life cycle for the bridges with emphasis on the maintenance scheduling. Moreover, Other types of more complicated neural networks could be used such as Narx non-linear dynamic series. More factors can be included in the design of experiments to design better models. More research would be carried out on the historical records for deterioration, to generate more information and parameters for the service life. This could be done by using ANN with another AI technique such as genetic algorithm or others. A wider set of BMS data to be modelled for historical records to detect patterns, then enhance the data to become a better reference. This field has a room for plenty of research and with the technology rapid development, new innovations are coming

References

1. Wellalage, N., Zhang, T. and Dwight, R. (2015). Calibrating Markov Chain–Based Deterioration Models for Predicting Future Conditions of Railway Bridge Elements. Journal of Bridge Engineering, 20(2), p.04014060.
2. Li, L., Sun, L. and Ning, G. (2014). Deterioration Prediction of Urban Bridges on Network Level Using Markov-Chain Model. Mathematical Problems in Engineering, 2014, pp.1-10
3. Agrawal, A., Kawaguchi, A. and Chen, Z. (2010). Deterioration Rates of Typical Bridge Elements in New York. Journal of Bridge Engineering, 15(4), pp.419-429.
4. Hovde, P.J. and Moser, K., 2004. Performance based methods for service life prediction. State of the art reports, CIB Report: Publication, 294.
5. Dekelbab, W., Al-Wazeer, A. & Harris, B. (2008). History Lessons From the National Bridge Inventory. United States Department of Transportation - Federal Highway Administration [online]. Vol. 71 (6), pp. 30-36. [Accessed 1 May 2017]. Available at:http://www.fhwa.dot.gov/publications/publicroads/08may/05.cfm
6. Ng, S. & Moses, F. (1998). Bridge deterioration modeling using semi-Markov theory. A. A. Balkema Uitgevers B. V, Structural Safety and Reliability, vol. 1, pp. 113-120
7. Jiang, Y. & Sinha, K. (1989). Bridge service life prediction model using the Markov chain. Transportation research record, vol. 1223, pp. 24-30
8. Pan, N., Lin, T. & Pan, N. (2009). Estimating bridge performance based on a matrix-driven fuzzy linear regression model. Automation in Construction, vol. 18 (5), pp. 578-586
9. Veshosky, D., Beidleman, C., Buetow, G. & Demir, M. (1994). Comparative Analysis of Bridge Superstructure Deterioration. Journal of Structural Engineering, vol. 120 (7), pp. 2123-2136.
10. Yanev, B. (1996). Optimal management and rehabilitation strategy for the bridges of New York City. In Proc. International Conference on Retrofitting of Structures, pp. 11-13
11. Yanev, B. & Testa, R. (1997). Life Cycle Performance of Bridge Components in New York City. Recent Advances in Bridge Engineering, pp. 385-392
12. Yanev, B. (1998). Bridge Management for New York City. Structural Engineering International, vol. 8 (3), pp. 211-215
13. Yanev, B. & chen, X. (1993). Life-cycle performance of New York City bridges. Transportation Research Record 1389, pp. 17-24

14. Sanders, D. & Zhang, Y. (1994). Bridge deterioration models for states with small bridge inventories. Transportation Research Record 1442, pp. 101-109

15. Abu Tair, A., McParland, C., Lyness, J. & Nadjai, A. (2002). Predictive models of deterioration rates of concrete bridges using the factor method based on historic inspection data. *9th International Conference on Durability of Building Materials and Components (DBMC)*. Australia. Brisbane
16. Aarseth, L. & Hovde, P. (1999). A stochastic approach to the factor method for estimating service life. Proceedings of the Eighth International Conference on Durability of Building Materials and Components. National Research Council Canada:Vancouver
17. Madanat, S. & Ibrahim, W. (1995). Poisson Regression Models of Infrastructure Transition Probabilities. Journal of Transportation Engineering, vol. 121 (3), pp. 267-272
18. Shahin, M., Nunez, M., Broten, M., Carpenter, S. & Sameh, A. (1987). New techniques for modeling pavement deterioration. Transportation Research Board.
19. Sianipar, P. & Adams, T. (1997). Fault-Tree Model of Bridge Element Deterioration Due to Interaction. Journal of Infrastructure Systems, vol. 3 (3), pp. 103-110
20. Mauch, M. & Madanat, S. (2001). Semiparametric Hazard Rate Models of Reinforced Concrete Bridge Deck Deterioration. Journal of Infrastructure Systems, vol. 7 (2), pp. 49-57.
21. Noortwijk, J. & Pandey, M. (2004). A stochastic deterioration process for time-dependent reliability analysis. In Proceedings of the Eleventh IFIP WG 7.5 Working Conference on Reliability and Optimization of Structural Systems. Canada. Banff.
22. Micevski, T., Kuczera, G. & Coombes, P. (2002). Markov Model for Storm Water Pipe Deterioration. Journal of Infrastructure Systems, vol. 8 (2), pp. 49-56
23. Morcous, G. (2006). Performance Prediction of Bridge Deck Systems Using Markov Chains. Journal of Performance of Constructed Facilities, vol. 20 (2), pp. 146-155.
24. Morcous, G., Lounis, Z. & Cho, Y. (2010). An integrated system for bridge management using probabilistic and mechanistic deterioration models: Application to bridge decks. KSCE Journal of Civil Engineering, vol. 14 (4), pp. 527-537

25. Powers, T. & Willis, T. (1950). The air requirement of frost resistant concrete. Highway Research Board Proceedings., vol. 29
26. chandra, S. & Berntsson, L. (2002). Lightweight aggregate concrete. Elsevier
27. Cabrera, J. (1996). Deterioration of concrete due to reinforcement steel corrosion. Cement and Concrete Composites, vol. 18 (1), pp. 47-59
28. Amleh, L. & Mirza, M. (2004). Corrosion Response of a Decommissioned Deteriorated Bridge Deck. Journal of Performance of Constructed Facilities, vol. 18 (4), pp. 185-194.
29. Powers, T. (1945). A working hypothesis for further studies of frost resistance of concrete. Journal of American Concrete Institute, vol. 41 (1), pp. 245-272
30. Powers, T. (1949). The air requirement of frost resistant concrete. Highway Research Board Proceedings, vol. 29, pp. 184-211
31. Powers, T. & Helmuth, R. (1953). Theory of volume changes in hardened portland cement paste during freezing Highway. Highway Research Board Proceedings, vol. 32, pp. 285-297
32. Beaudoin, J. & MacInnis, C. (1974). The mechanism of frost damage in hardened cement paste. Cement and Concrete Research, vol. 4 (2), pp. 139-147
33. Jacobsen, S., Sellevold, E. & Matala, S. (1996). Frost durability of high strength concrete: Effect of internal cracking on ice formation. Cement and Concrete Research, vol. 26 (6), pp. 919-931
34. Cai, H. & Liu, X. (1998). Freeze-thaw durability of concrete: ice formation process in pores. Cement and Concrete Research, vol. 28 (9), pp. 1281-1287
35. COUSSY, O. (2005). Poromechanics of freezing materials. Journal of the Mechanics and Physics of Solids, vol. 53 (8), pp. 1689-1718
36. Mehta, N. & Monteiro, P. (2006). Concrete. New York, NY:McGraw-Hill
37. Basheer, P., Chidiact, S. & Long, A. (1996). Predictive models for deterioration of concrete structures. Construction and Building Materials, vol. 10 (1), pp. 27-37.
38. Saetta, A., Schrefler, B. & Vitaliani, R. (1993). The carbonation of concrete and the mechanism of moisture, heat and carbon dioxide flow through porous materials. Cement and Concrete Research, vol. 23 (4), pp. 761-772.
39. Rozière, E., Loukili, A. & Cussigh, F. (2009). A performance based approach for durability of concrete exposed to carbonation. Construction and Building Materials, vol. 23 (1), pp. 190-199
40. Papadakis, V., Vayenas, C. & Fardis, M. (1989). A reaction engineering approach to the problem of concrete carbonation. AIChE Journal, vol. 35 (10), pp. 1639-1650.

41. Houst, Y. & Wittmann, F. (2002). Depth profiles of carbonates formed during natural carbonation. Cement and Concrete Research, vol. 32 (12), pp. 1923-1930.
42. Collepardi, M. (2003). A state-of-the-art review on delayed ettringite attack on concrete. Cement and Concrete Composites, vol. 25 (4-5), pp. 401-407
43. Neville, A. (2004). The confused world of sulfate attack on concrete. Cement and Concrete Research, vol. 34 (8), pp. 1275-1296
44. Marchand, J., Odler, I. & Skalny, J. (2003). Sulfate attack on concrete. CRC Press.
45. Hobbs, D. (1988). Alkali-Silica Reaction in Concrete. London:Thomas Telford.
46. Swamy, R. (2003). Alkali-silica reaction in concrete. Glasgow, England:Blackie and Son.
47. Almusallam, A., Al-Gahtani, A., Aziz, A. & Rasheeduzzafar. (1996). Effect of reinforcement corrosion on bond strength. Construction and Building Materials, vol. 10 (2), pp. 123-129
48. BRE Digest 444(2000), Corrosion of steel in concrete . Durability of reinforced concrete structures, part I, BRE centre for concrete construction, bre press.
49. Neville, A. (1995). Chloride attack of reinforced concrete: an overview. Materials and Structures, vol. 28 (2), pp. 63-70.
50. West, G. (1996). Alkali-aggregate reaction in concrete roads and bridges. London:Thomas Telford.
51. Bu, G., Lee, J., Guan, H., Loo, Y. & Blumenstein, M. (2014). Implementation of Elman neural networks for enhancing reliability of integrated bridge deterioration model. *Australian Journal of Structural Engineering*, vol. 15 (1).
52. Callow, D., Lee, J., Blumenstein, M., Guan, H. & Loo, Y.-C. (2013). Development of hybrid optimisation method for artificial intelligence based bridge deterioration model — feasibility study. *Automation in Construction*, vol. 31, pp. 83–91.
53. Chen, Z., Wu, Y., Li, L. & Sun, L. (2015). Application of artificial intelligence for bridge deterioration model. *The Scientific World Journal*, vol. 2015, pp. 1–6.
54. Firouzi, A. & Rahai, A. (2012). An integrated ANN-GA for reliability based inspection of concrete bridge decks considering extent of corrosion-induced cracks and life cycle costs. *Scientia Iranica*, vol. 19 (4), pp. 974–981.
55. Huang, Y.-H. (2010). Artificial neural network model of bridge deterioration. *Journal of Performance of Constructed Facilities*, vol. 24 (6), pp. 597–602.
56. Milne, P.H. (1989). The application of artificial intelligence techniques to civil and structural engineering. *Artificial Intelligence in Engineering*, vol. 4 (1), pp. 54–55.

57. Morcous, G., Rivard, H. & Hanna, A.M. (2002). Modeling bridge deterioration using case-based reasoning. *Journal of Infrastructure Systems*, vol. 8 (3), pp. 86–95.
58. [Accessed 22 September 2016]. Available at: http://10.4028/www.scientific.net/amm.99-100.444
59. Kobbacy, K.A.H. (2012). Application of artificial intelligence in maintenance Modelling and management. *IFAC Proceedings Volumes*, vol. 45 (31), pp. 54–59.
60. Smarsly, K., lehner, K. & Hartmann, D. (2007). Structural Health Monitoring based on Artificial Intelligence Techniques. *Computing in Engineering*
61. GHOSH-DASTIDAR, S. & ADELI, H. (2009). SPIKING NEURAL NETWORKS. *International Journal of Neural Systems*, vol. 19 (04), pp. 295–308.
62. Dreyfus, G., Dreyfus, G. & Dreyfus, rard G. (2004). *Neural networks: Methodology and applications*. Berlin:Springer-Verlag Berlin and Heidelberg GmbH & Co. K.
63. Gupta, M.M., Jin, L. & Homma, N. (2003). *Static and dynamic neural networks: From fundamentals to advanced theory*. New York, NY, United States:Wiley-Interscience
64. Boden, M. (2001). A guide to recurrent neural networks and backpropagation. *Halmstad University*.
65. Tang, H., Tan, K.C.C., Zhang, Y. & Yi, Z. (2007). *Neural networks: Computational models and applications ; with 27 tables*. Berlin:Springer-Verlag Berlin and Heidelberg GmbH & Co. K
66. Lu, P., Chen, S. & Zheng, Y. (2012). Artificial Intelligence in Civil Engineering. Mathematical Problems in Engineering 2012

67. lee, J., Guan, H., Chaye loo, Y., Blumenstein, M. & Xin ping, W. (2011). Modelling Long-term Bridge Deterioration at Structural Member Level Using Artificial Intelligence Techniques. [Accessed 25 September 2016]. Available at: http://10.4028/www.scientific.net/amm.99-100.444

68. SONG, Y. & PENG, X. (2011). MODELING METHOD USING COMBINED ARTIFICIAL NEURAL NETWORK. *International Journal of Computational Intelligence and Applications*, vol. 10 (02), pp. 189–198
69. Kabir, S., Rivard, P. & Ballivy, G. (2008). Neural-network-based damage classification of bridge infrastructure using texture analysis. *Canadian Journal of Civil Engineering*, vol. 35 (3), pp. 258–267.
70. Huang, Y.-H. (2010b). Artificial neural network model of bridge deterioration. *Journal of Performance of Constructed Facilities*, vol. 24 (6), pp. 597–602
71. Pang, Y., Dang, X. & Yuan, W. (2014). An artificial neural network based method for seismic fragility analysis of highway bridges. *Advances in Structural Engineering*, vol. 17 (3), pp. 413–428.
72. Chun, P., Yamashita, H. & Furukawa, S. (2015). Bridge damage severity quantification using Multipoint acceleration measurement and artificial neural networks.*Shock and Vibration*, vol. 2015, pp. 1–11.
73. Russell, S.J. & Norvig, P. (2010). *Artificial intelligence: A modern approach*. United Kingdom:Prentice Hall

74. Moazami, D., Behbahani, H. & Muniandy, R. (2011). Pavement rehabilitation and maintenance prioritization of urban roads using fuzzy logic. *Expert Systems with Applications*, vol. 38 (10), pp. 12869–12879
75. Khan, F.I., Sadiq, R. & Haddara, M.M. (2004). Risk-based inspection and maintenance (RBIM). *Process Safety and Environmental Protection*, vol. 82 (6), pp. 398–411
76. Cheng, Z., Jia, X., Gao, P., Wu, S. & Wang, J. (2008). A framework for intelligent reliability centered maintenance analysis. *Reliability Engineering & System Safety*, vol. 93 (6), pp. 806–814.
77. Senouci, A. & Al-Derham, H.R. (2008). Genetic algorithm-based multi-objective model for scheduling of linear construction projects. *Advances in Engineering Software*, vol. 39 (12), pp1023–1028.
78. Law, C. (2016). *Data mining*. Wikimedia Foundation. [Accessed 2 October 2016]. Available at: https://en.wikipedia.org/wiki/Data_mining
79. *Expert system*. (2016). Wikimedia Foundation. [Accessed 2 October 2016]. Available at: https://en.wikipedia.org/wiki/Expert_system
80. Marwala, T. & Patel, P.B. (2006). Forecasting Closing Price Indices Using Neural Networks. *IEEE Conference on Systems, Man, and Cybernet Taipei, Taiwan,ics*, pp. 2351–2356, 2006
81. Masoud, N. (2014). Predicting direction of stock prices index movement using artificial neural networks: The case of Libyan financial market. *British Journal of Economics, Management & Trade*, vol. 4 (4), pp. 597–619
82. Hornik, K., Stinchcombe, M. & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, vol. 2 (5), pp. 359–366
83. Elhag, T. M. S., Boussabaine, A. H., & Ballal, T. M. A. (2005). Critical determinants of construction tendering costs: Quantity surveyors' standpoint.*International Journal of Project Management*, *23*(7), 538-545.
84. Lee, J., Guan, H., Loo, Y. and Blumenstein, M. (2014). Development of a Long-Term Bridge Element Performance Model Using Elman Neural Networks. Journal of Infrastructure Systems, 20(3), p.04014013
85. Haykin, S. (1999). *Neural networks A Comprehensive Foundation*. 2nd ed. Delhi: Pearson Education
86. Kriesel, D. (2007). A Brief Introduction to Neural Networks.
87. Kobbacy, K., Vadera, S. & Rasmy, M. (2006). AI and OR in management of operations: history and trends. Journal of the Operational Research Society, vol. 58 (1), pp. 10-28
88. Michalski, R., Jaime, C. & Mitchell, T. (2013). Machine learning: An artificial intelligence approach. Springer Science & Business Media.
89. Flood, I. (2008). Towards the next generation of artificial neural networks for civil engineering. Advanced Engineering Informatics, vol. 22 (1), pp. 4-14.
90. Arel, I., Rose, D. & Karnowski, T. (2010). Deep Machine Learning - A New Frontier in Artificial Intelligence Research [Research Frontier]. IEEE Computational Intelligence Magazine, vol. 5 (4), pp. 13-18.
91. Shi, Z. & Zheng, N. (2006). Progress and Challenge of Artificial Intelligence. Journal of Computer Science and Technology, vol. 21 (5), pp. 810-822.
92. Gurney, K. (1999). An introduction to neural networks. London:Routledge.
93. Hagan, M., Demuth, H., Beale, M. & De Jesus, O. (2014). Neural Network Design. 2nd edn.

94. Hornik, K., Stinchcombe, M. & White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks, vol. 2 (5), pp. 359-366
95. Box, G., Jenkins, G. & Reinsel, G. (2008). Time Series Analysis: Forecasting and Control. 4th edn. Wiley.
96. Hagan, M., Demuth, H. & Jesús, O. (2002). An introduction to the use of neural networks in control systems. International Journal of Robust and Nonlinear Control, vol. 12 (11), pp. 959-985.
97. Fausett, L. (1994). Fundamentals of Neural Networks: Architectures, Algorithms, and Applications. Prentice-Hall

Bibliography

1. Huang, R., Mao, I. and Lee, H. (2010). Exploring the Deterioration Factors of RC Bridge Decks: A Rough Set Approach. Computer-Aided Civil and Infrastructure Engineering, 25(7), pp.517-529
2. Yang, Y., Pam, H. and Kumaraswamy, M. (2009). Framework Development of Performance Prediction Models for Concrete Bridges. Journal of Transportation Engineering, 135(8), pp.545-554.
3. Morcous, G., Lounis, Z. and Mirza, M. (2003). Identification of Environmental Categories for Markovian Deterioration Models of Bridge Decks. Journal of Bridge Engineering, 8(6), pp.353-361
4. Cesare, M., Santamarina, C., Turkstra, C. and Vanmarcke, E. (1992). Modeling Bridge Deterioration with Markov Chains. Journal of Transportation Engineering, 118(6), pp.820-833.
5. Šomodíková, M., Lehký, D., Doležel, J. and Novák, D. (2016). Modeling of degradation processes in concrete: Probabilistic lifetime and load-bearing capacity assessment of existing reinforced concrete bridges. Engineering Structures, 119, pp.49-60.
6. Michel, A., Stang, H., Lepech, M. and Geiker, M. (2015). Multi-Physics and Multi-Scale Deterioration Modelling of Reinforced Concrete. Key Engineering Materials, 665, pp.13-16
7. Madanat, S., Karlaftis, M. and McCarthy, P. (1997). Probabilistic Infrastructure Deterioration Models with Panel Data. Journal of Infrastructure Systems, 3(1), pp.4-9.
8. Bastidas-Arteaga, E., Bressolette, P., Chateauneuf, A. and Sánchez-Silva, M. (2009). Probabilistic lifetime assessment of RC structures under coupled corrosion–fatigue deterioration processes. Structural Safety, 31(1), pp.84-96.
9. Frangopol, D., Kallen, M. and Noortwijk, J. (2004). Probabilistic models for life-cycle performance of deteriorating structures: review and future directions. Progress in Structural Engineering and Materials, 6(4), pp.197-212.

10. Chiu, C., Lyu, Y. and Jean, W. (2013). Probability-based damage assessment for reinforced concrete bridge columns considering the corrosive and seismic hazards in Taiwan. Natural Hazards, 71(3), pp.2143-2164.
11. Sobanjo, J., Mtenga, P. and Rambo-Roddenberry, M. (2010). Reliability-Based Modeling of Bridge Deterioration Hazards. Journal of Bridge Engineering, 15(6), pp.671-683
12. Podroužek, J., Strauss, A. and Bergmeister, K. (2014). Robustness-based performance assessment of a prestressed concrete bridge. Structural Concrete, 15(2), pp.248-257.
13. Caner, A., Yanmaz, A., Yakut, A., Avsar, O. and Yilmaz, T. (2008). Service Life Assessment of Existing Highway Bridges with No Planned Regular Inspections. Journal of Performance of Constructed Facilities, 22(2), pp.108-114

Appendix A

This Appendix contains the processed bridge database that is used for neural network training. A total of 221 number of input rows as shown below

Bridge Type	Exposure	Member	Defect	Age
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	25
FootBridge	Mild	Flexural	Minor	25
FootBridge	Mild	Flexural	Minor	30
FootBridge	Mild	Flexural	Minor	15
FootBridge	Mild	Flexural	Minor	30
FootBridge	Mild	Compression	Minor	30
FootBridge	Mild	Compression	Minor	10
FootBridge	Mild	Compression	Minor	10
FootBridge	Mild	Compression	Minor	10
FootBridge	Mild	Flexural	Major	20
FootBridge	Mild	Flexural	Major	15
FootBridge	Mild	Flexural	Major	15
FootBridge	Mild	Flexural	Major	30
FootBridge	Mild	Flexural	Major	30
FootBridge	Mild	Flexural	Major	40
FootBridge	Mild	Flexural	Major	15
FootBridge	Mild	Flexural	Major	40
FootBridge	Mild	Flexural	Major	25
FootBridge	Mild	Flexural	Major	35
FootBridge	Mild	Compression	Major	15
FootBridge	Mild	Compression	Major	15
FootBridge	Mild	Compression	Major	10
FootBridge	Mild	Flexural	Spalling	35
FootBridge	Mild	Flexural	Spalling	20
FootBridge	Mild	Flexural	Spalling	20
FootBridge	Mild	Flexural	Spalling	40
FootBridge	Mild	Flexural	Spalling	25
FootBridge	Mild	Flexural	Spalling	45
FootBridge	Mild	Flexural	Spalling	45
FootBridge	Mild	Compression	Spalling	64
FootBridge	Mild	Compression	Spalling	20
FootBridge	Mild	Flexural	Service Failure	55

Bridge Type	Exposure	Member	Defect	Age
FootBridge	Mild	Flexural	Service Failure	50
FootBridge	Mild	Flexural	Service Failure	50
FootBridge	Mild	Compression	Service Failure	25
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	20
FootBridge	Moderate	Flexural	Minor	20
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	20
FootBridge	Moderate	Flexural	Minor	35
FootBridge	Moderate	Flexural	Minor	25
FootBridge	Moderate	Flexural	Minor	25
FootBridge	Moderate	Flexural	Minor	25
FootBridge	Moderate	Flexural	Minor	30
FootBridge	Moderate	Flexural	Minor	20
FootBridge	Moderate	Flexural	Minor	25
FootBridge	Moderate	Flexural	Minor	25
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	15
FootBridge	Moderate	Flexural	Minor	30
FootBridge	Moderate	Compression	Minor	20
FootBridge	Moderate	Compression	Minor	55
FootBridge	Moderate	Compression	Minor	25
FootBridge	Moderate	Compression	Minor	30
FootBridge	Moderate	Compression	Minor	55
FootBridge	Moderate	Compression	Minor	55
FootBridge	Moderate	Compression	Minor	45
FootBridge	Moderate	Compression	Minor	20
FootBridge	Moderate	Compression	Minor	40
FootBridge	Moderate	Compression	Minor	40
FootBridge	Moderate	Flexural	Major	30
FootBridge	Moderate	Flexural	Major	25
FootBridge	Moderate	Flexural	Major	40
FootBridge	Moderate	Flexural	Major	30
FootBridge	Moderate	Flexural	Major	25
FootBridge	Moderate	Flexural	Major	20
FootBridge	Moderate	Flexural	Major	20
FootBridge	Moderate	Flexural	Major	45
FootBridge	Moderate	Flexural	Major	35
FootBridge	Moderate	Flexural	Major	30
FootBridge	Moderate	Flexural	Major	40
FootBridge	Moderate	Flexural	Major	25

Bridge Type	Exposure	Member	Defect	Age
FootBridge	Moderate	Flexural	Major	35
FootBridge	Moderate	Flexural	Major	40
FootBridge	Moderate	Flexural	Major	20
FootBridge	Moderate	Flexural	Major	20
FootBridge	Moderate	Flexural	Major	40
FootBridge	Moderate	Compression	Major	30
FootBridge	Moderate	Compression	Major	35
FootBridge	Moderate	Compression	Major	40
FootBridge	Moderate	Compression	Major	60
FootBridge	Moderate	Compression	Major	55
FootBridge	Moderate	Compression	Major	25
FootBridge	Moderate	Compression	Major	45
FootBridge	Moderate	Compression	Major	45
FootBridge	Moderate	Flexural	Spalling	40
FootBridge	Moderate	Flexural	Spalling	35
FootBridge	Moderate	Flexural	Spalling	50
FootBridge	Moderate	Flexural	Spalling	20
FootBridge	Moderate	Flexural	Spalling	30
FootBridge	Moderate	Flexural	Spalling	25
FootBridge	Moderate	Flexural	Spalling	30
FootBridge	Moderate	Flexural	Spalling	45
FootBridge	Moderate	Flexural	Spalling	50
FootBridge	Moderate	Flexural	Spalling	25
FootBridge	Moderate	Flexural	Spalling	40
FootBridge	Moderate	Flexural	Spalling	50
FootBridge	Moderate	Flexural	Spalling	25
FootBridge	Moderate	Flexural	Spalling	35
FootBridge	Moderate	Compression	Spalling	40
FootBridge	Moderate	Compression	Spalling	45
FootBridge	Moderate	Compression	Spalling	55
FootBridge	Moderate	Compression	Spalling	60
FootBridge	Moderate	Compression	Spalling	60
FootBridge	Moderate	Compression	Spalling	50
FootBridge	Moderate	Flexural	Service Failure	35
FootBridge	Moderate	Flexural	Service Failure	15
FootBridge	Moderate	Compression	Service Failure	50
FootBridge	Moderate	Compression	Service Failure	55
FootBridge	Severe	Flexural	Minor	25
FootBridge	Severe	Flexural	Minor	50
FootBridge	Severe	Flexural	Minor	45
FootBridge	Severe	Flexural	Minor	40
FootBridge	Severe	Flexural	Minor	30
FootBridge	Severe	Flexural	Minor	25

Bridge Type	Exposure	Member	Defect	Age
FootBridge	Severe	Compression	Minor	55
FootBridge	Severe	Compression	Minor	50
FootBridge	Severe	Compression	Minor	30
FootBridge	Severe	Flexural	Major	30
FootBridge	Severe	Flexural	Major	55
FootBridge	Severe	Flexural	Major	50
FootBridge	Severe	Flexural	Major	50
FootBridge	Severe	Flexural	Major	30
FootBridge	Severe	Compression	Major	55
FootBridge	Severe	Flexural	Spalling	35
FootBridge	Severe	Flexural	Spalling	55
FootBridge	Severe	Compression	Spalling	55
Overbridge	Mild	Flexural	Minor	20
Overbridge	Mild	Flexural	Minor	20
Overbridge	Mild	Flexural	Minor	15
Overbridge	Mild	Flexural	Minor	40
Overbridge	Mild	Flexural	Minor	35
Overbridge	Mild	Flexural	Minor	30
Overbridge	Mild	Compression	Minor	10
Overbridge	Mild	Compression	Minor	35
Overbridge	Mild	Compression	Minor	15
Overbridge	Mild	Compression	Minor	20
Overbridge	Mild	Flexural	Major	15
Overbridge	Mild	Flexural	Major	25
Overbridge	Mild	Flexural	Major	15
Overbridge	Mild	Flexural	Major	45
Overbridge	Mild	Flexural	Major	45
Overbridge	Mild	Flexural	Major	40
Overbridge	Mild	Compression	Major	20
Overbridge	Mild	Compression	Major	25
Overbridge	Mild	Flexural	Spalling	20
Overbridge	Mild	Flexural	Spalling	30
Overbridge	Mild	Flexural	Spalling	20
Overbridge	Mild	Flexural	Spalling	55
Overbridge	Mild	Compression	Spalling	25
Overbridge	Mild	Flexural	Service Failure	30
Overbridge	Mild	Flexural	Service Failure	35
Overbridge	Mild	Flexural	Service Failure	60
Overbridge	Moderate	Flexural	Minor	25
Overbridge	Moderate	Flexural	Minor	40
Overbridge	Moderate	Flexural	Minor	35
Overbridge	Moderate	Flexural	Minor	10
Overbridge	Moderate	Flexural	Minor	10

Bridge Type	Exposure	Member	Defect	Age
Overbridge	Moderate	Flexural	Minor	10
Overbridge	Moderate	Flexural	Minor	25
Overbridge	Moderate	Flexural	Minor	25
Overbridge	Moderate	Flexural	Minor	15
Overbridge	Moderate	Compression	Minor	35
Overbridge	Moderate	Compression	Minor	55
Overbridge	Moderate	Compression	Minor	45
Overbridge	Moderate	Compression	Minor	60
Overbridge	Moderate	Compression	Minor	55
Overbridge	Moderate	Compression	Minor	35
Overbridge	Moderate	Flexural	Major	30
Overbridge	Moderate	Flexural	Major	55
Overbridge	Moderate	Flexural	Major	55
Overbridge	Moderate	Flexural	Major	50
Overbridge	Moderate	Flexural	Major	45
Overbridge	Moderate	Flexural	Major	20
Overbridge	Moderate	Flexural	Major	15
Overbridge	Moderate	Flexural	Major	15
Overbridge	Moderate	Flexural	Major	35
Overbridge	Moderate	Flexural	Major	35
Overbridge	Moderate	Flexural	Major	20
Overbridge	Moderate	Compression	Major	15
Overbridge	Moderate	Compression	Major	25
Overbridge	Moderate	Compression	Major	40
Overbridge	Moderate	Flexural	Spalling	35
Overbridge	Moderate	Flexural	Spalling	20
Overbridge	Moderate	Flexural	Spalling	20
Overbridge	Moderate	Flexural	Spalling	40
Overbridge	Moderate	Compression	Spalling	15
Overbridge	Moderate	Compression	Spalling	45
Overbridge	Moderate	Flexural	Service Failure	50
Overbridge	Moderate	Compression	Service Failure	15
Overbridge	Severe	Flexural	Minor	30
Overbridge	Severe	Flexural	Minor	20
Overbridge	Severe	Flexural	Minor	10
Overbridge	Severe	Flexural	Minor	40
Overbridge	Severe	Flexural	Minor	50
Overbridge	Severe	Compression	Minor	30
Overbridge	Severe	Compression	Minor	30
Overbridge	Severe	Compression	Minor	20
Overbridge	Severe	Flexural	Major	35
Overbridge	Severe	Flexural	Major	50
Overbridge	Severe	Flexural	Major	45

Bridge Type	Exposure	Member	Defect	Age
Overbridge	Severe	Flexural	Major	60
Overbridge	Severe	Compression	Major	35
Overbridge	Severe	Compression	Major	25
Overbridge	Severe	Flexural	Spalling	40
Overbridge	Severe	Flexural	Spalling	20
Overbridge	Severe	Compression	Spalling	35
Overbridge	Severe	Compression	Spalling	40
Overbridge	Severe	Compression	Spalling	30
Overbridge	Severe	Flexural	Service Failure	40
Overbridge	Severe	Compression	Service Failure	40

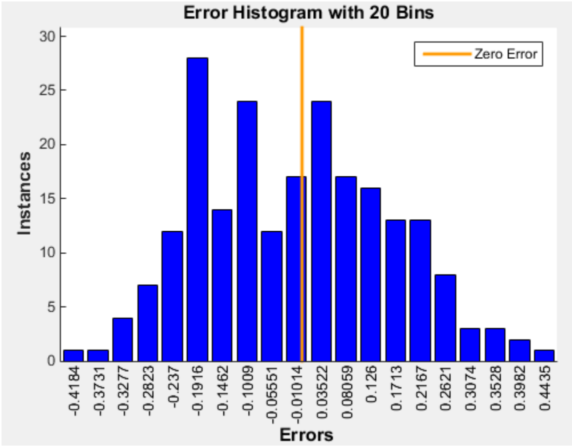
Table A.1 demonstrates the deterioration scenarios with the correspondent standard deviation for each one. The standard deviation provides information on the data status and insight on the randomness degree

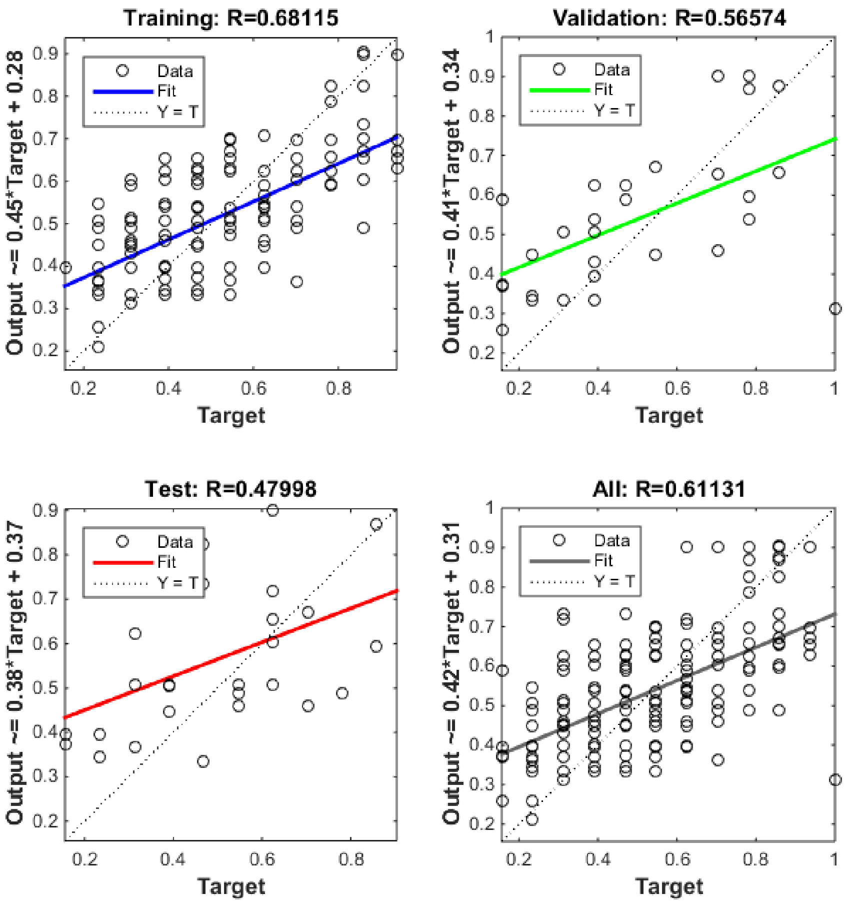
Bridge	Exposure	Member	Minor	Major	Spalling	Service Failure
Footbridge	Mild	Flexural	6.2	9.5	10.3	2.36
Footbridge	Moderate	Flexural	6.01	8.2	9.97	10
Footbridge	Severe	Flexural	9.75	10.77	10	-
Footbridge	Mild	Compression	8.66	2.36	22	-
Footbridge	Moderate	Compression	13.43	11.16	7.45	2.5
Footbridge	Severe	Compression	10.8	-	-	-
Overbridge	Mild	Flexural	8.98	13.04	14.31	13.12
Overbridge	Moderate	Flexural	10.54	14.74	8.93	-
Overbridge	Severe	Flexural	9.9	10.27	15	-
Overbridge	Mild	Compression	9.35	2.5	-	-
Overbridge	Moderate	Compression	9.9	10.27	15	-
Overbridge	Severe	Compression	4.71	5	4.08	-

Table A.1: Standard deviation for Deterioration Scenarios

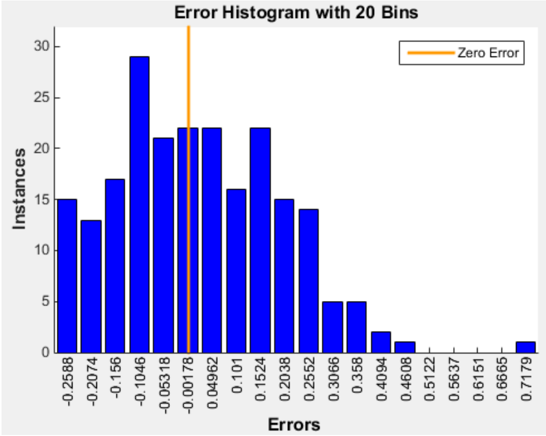
Appendix B

Model 1

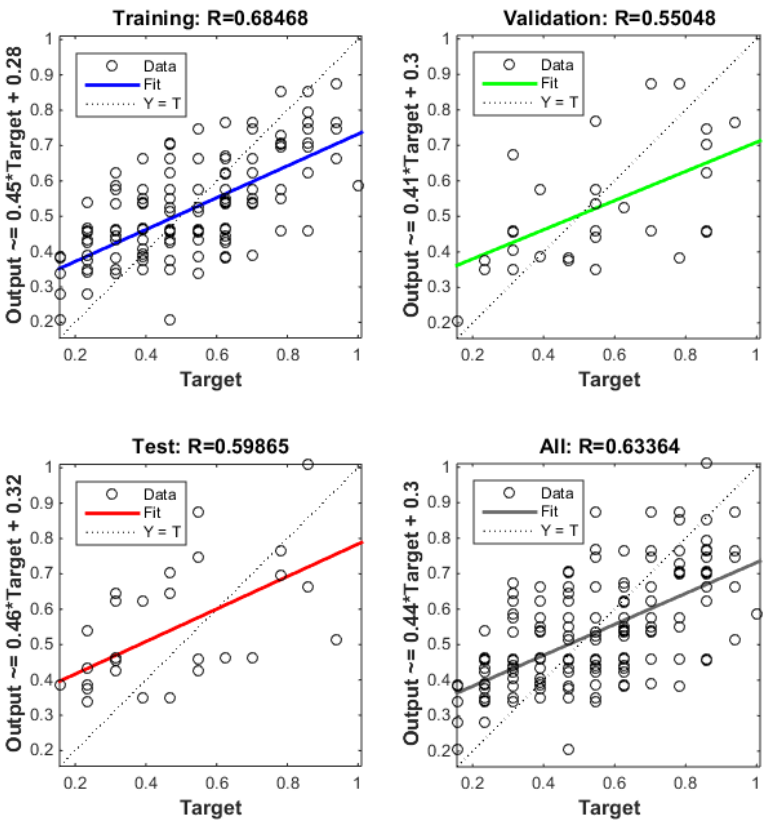




Model 2

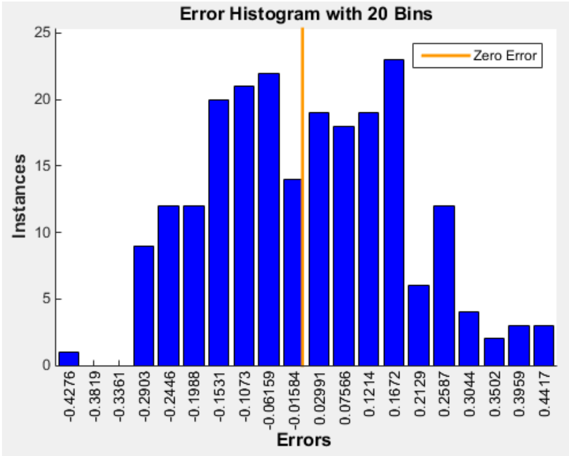


Error Histogram with 20 Bins
Zero Error
Instances
Errors

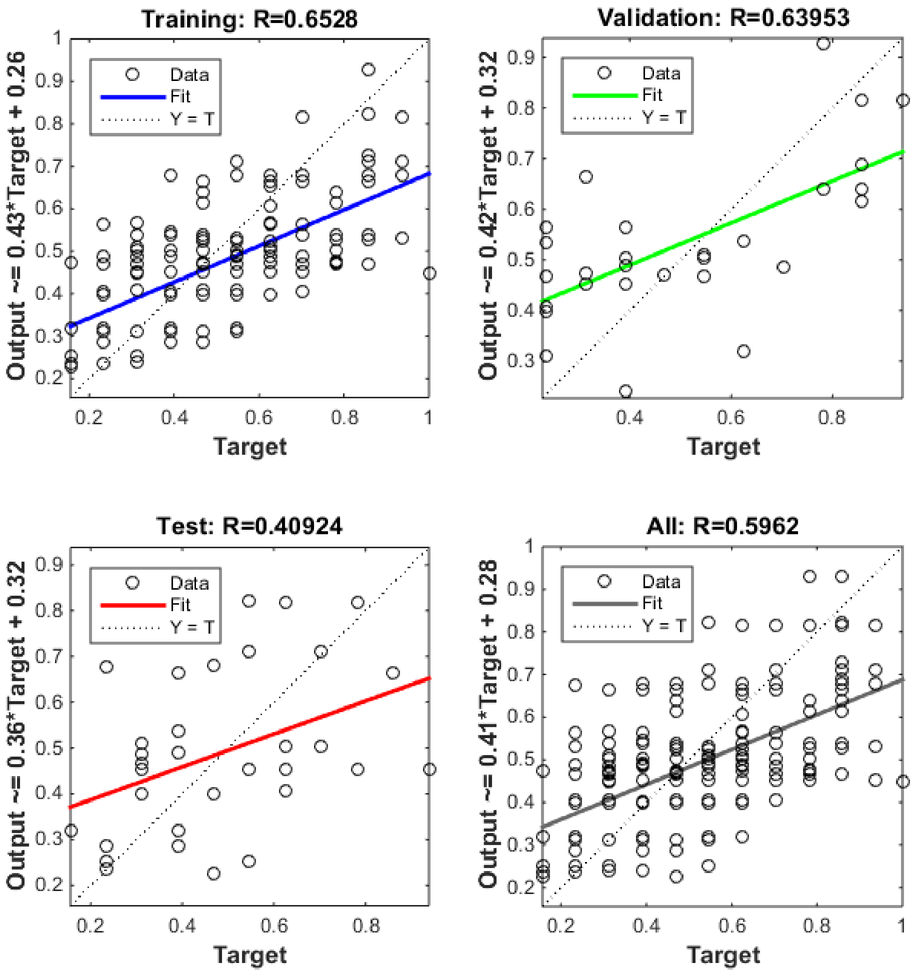


Training: R=0.68468
Validation: R=0.55048
Test: R=0.59865
All: R=0.63364
Output ~= 0.45*Target + 0.28
Output ~= 0.41*Target + 0.3
Output ~= 0.46*Target + 0.32
Output ~= 0.44*Target + 0.3
Data
Fit
Y = T
Target

Model 3

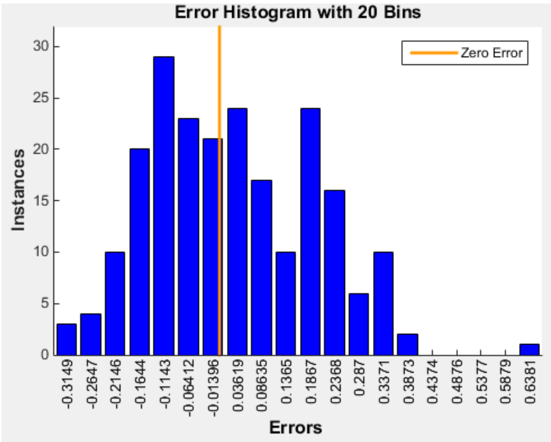


Error Histogram with 20 Bins
Zero Error
Instances
Errors

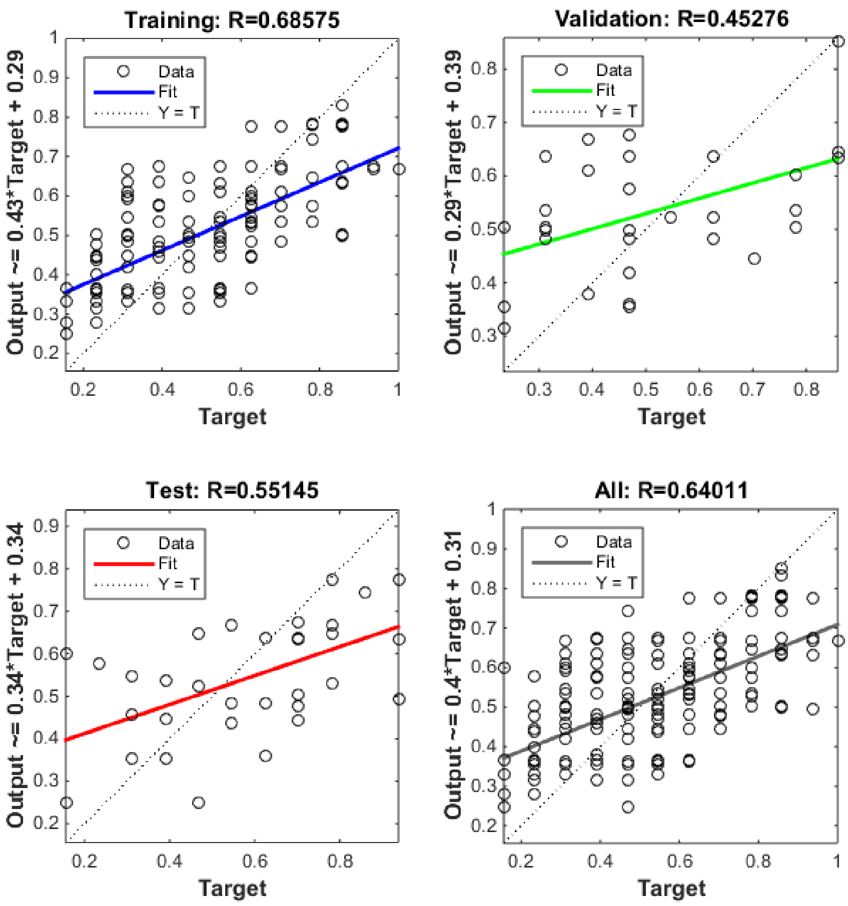


Training: R=0.6528
Output ~= 0.43*Target + 0.26
Validation: R=0.63953
Output ~= 0.42*Target + 0.32
Test: R=0.40924
Output ~= 0.36*Target + 0.32
All: R=0.5962
Output ~= 0.41*Target + 0.28
Data
Fit
Y = T
Target

Model 4

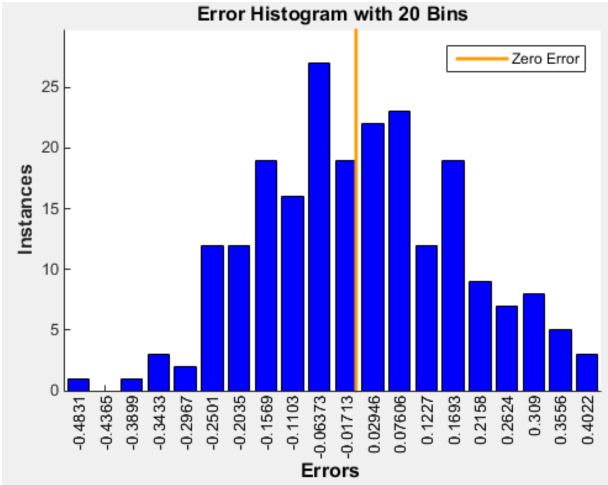


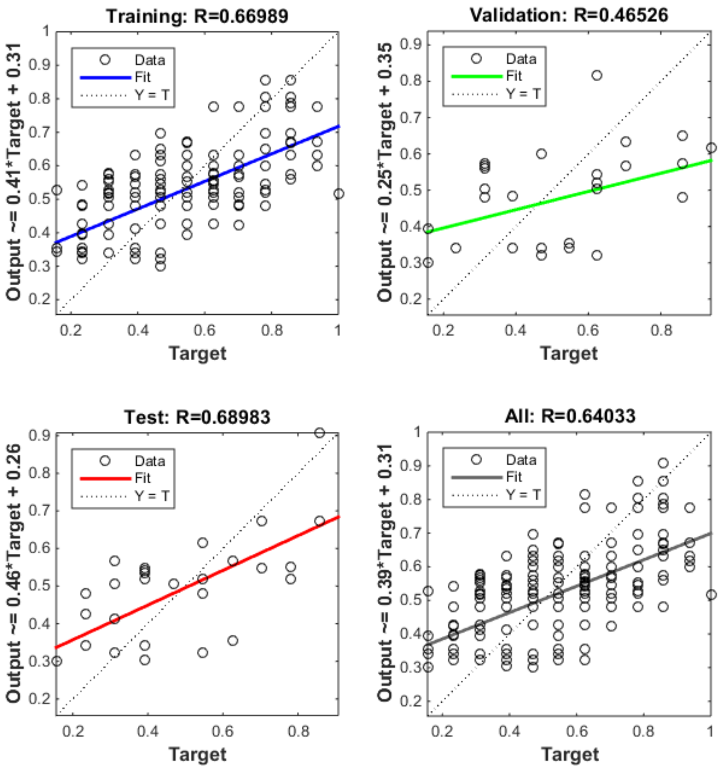
Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.3149
-0.2647
-0.2146
-0.1644
-0.1143
-0.06412
-0.01396
0.03619
0.08635
0.1365
0.1867
0.2368
0.287
0.3371
0.3873
0.4374
0.4876
0.5377
0.5879
0.6381



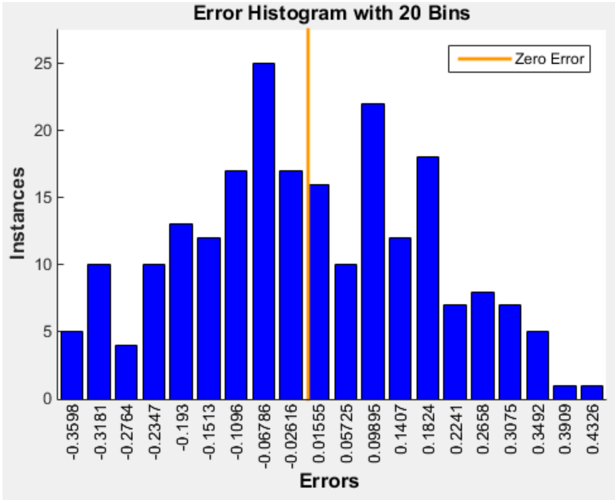
Training: R=0.68575
Output ~= 0.43*Target + 0.29
Validation: R=0.45276
Output ~= 0.29*Target + 0.39
Test: R=0.55145
Output ~= 0.34*Target + 0.34
All: R=0.64011
Output ~= 0.4*Target + 0.31
Data
Fit
Y = T
Target

Model 5

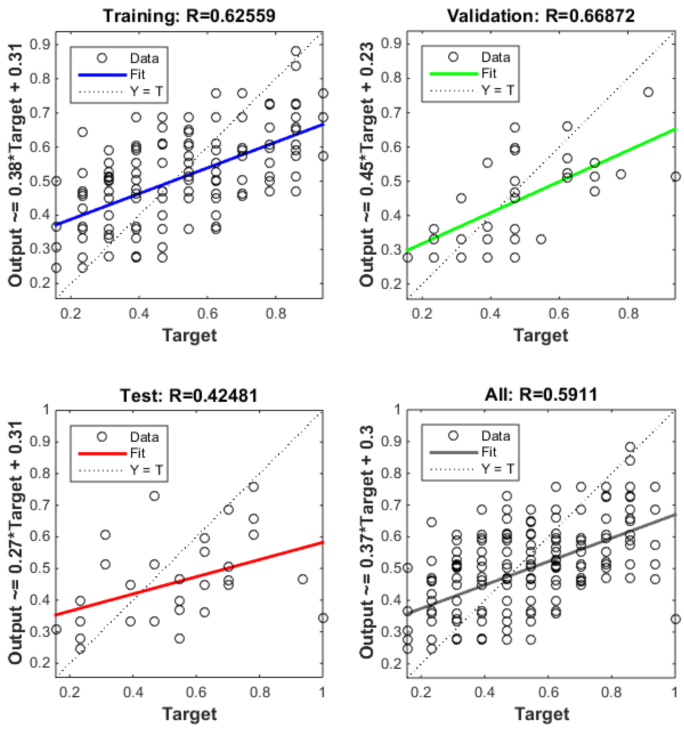

Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.4831
-0.4365
-0.3899
-0.3433
-0.2967
-0.2501
-0.2035
-0.1569
-0.1103
-0.06373
-0.01713
0.02946
0.07606
0.1227
0.1693
0.2158
0.2624
0.309
0.3556
0.4022


Training: R=0.66989
Output ~= 0.41*Target + 0.31
Validation: R=0.46526
Output ~= 0.25*Target + 0.35
Test: R=0.68983
Output ~= 0.46*Target + 0.26
All: R=0.64033
Output ~= 0.39*Target + 0.31
Data
Fit
Y = T
Target

Model 6

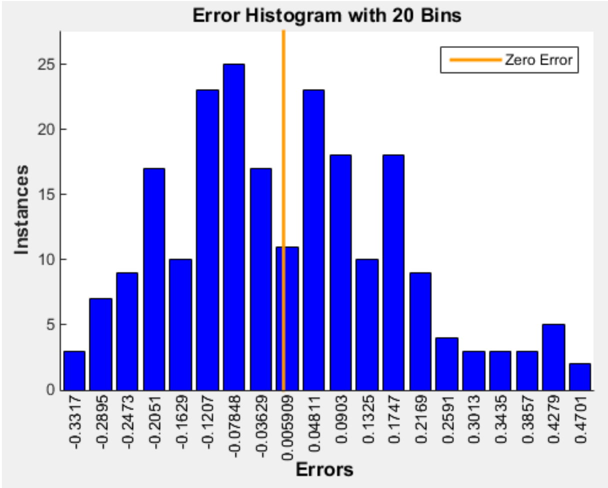


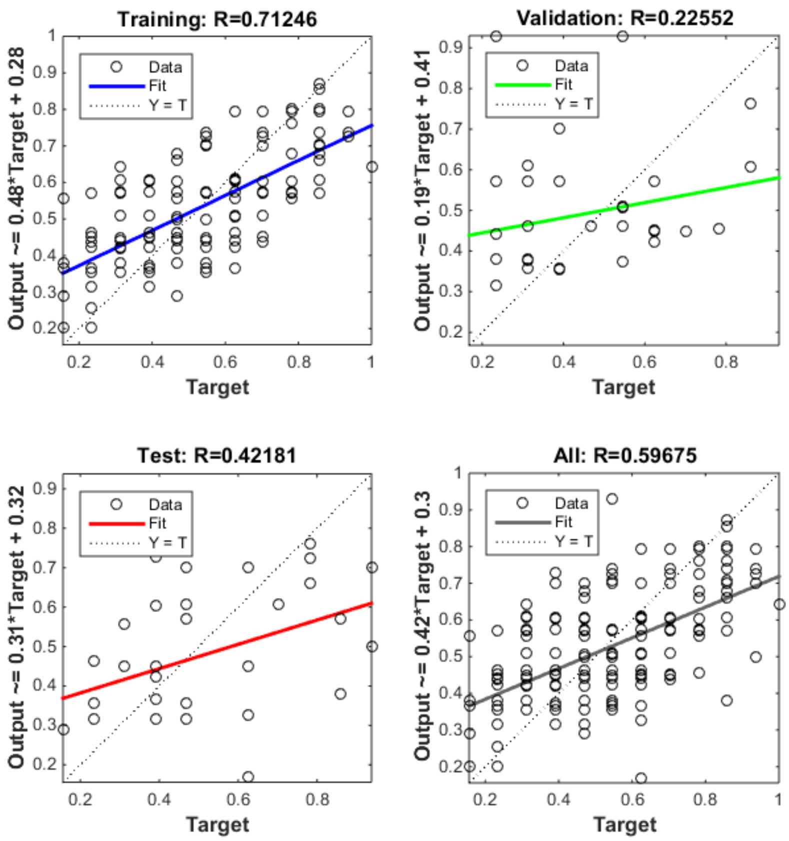
Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.3598
-0.3181
-0.2764
-0.2347
-0.193
-0.1513
-0.1096
-0.06786
-0.02616
0.01555
0.05725
0.09895
0.1407
0.1824
0.2241
0.2658
0.3075
0.3492
0.3909
0.4326



Training: R=0.62559
Output ~= 0.38*Target + 0.31
Validation: R=0.66872
Output ~= 0.45*Target + 0.23
Test: R=0.42481
Output ~= 0.27*Target + 0.31
All: R=0.5911
Output ~= 0.37*Target + 0.3
Data
Fit
Y = T
Target

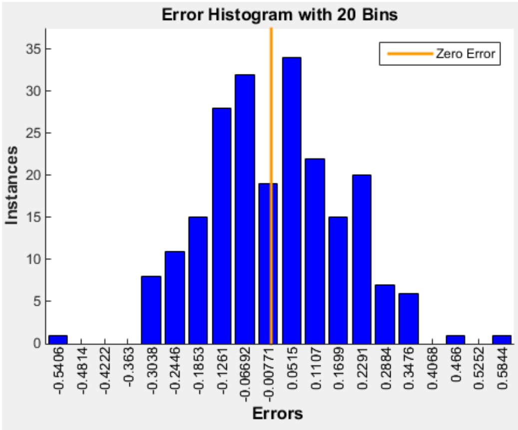
Model 7



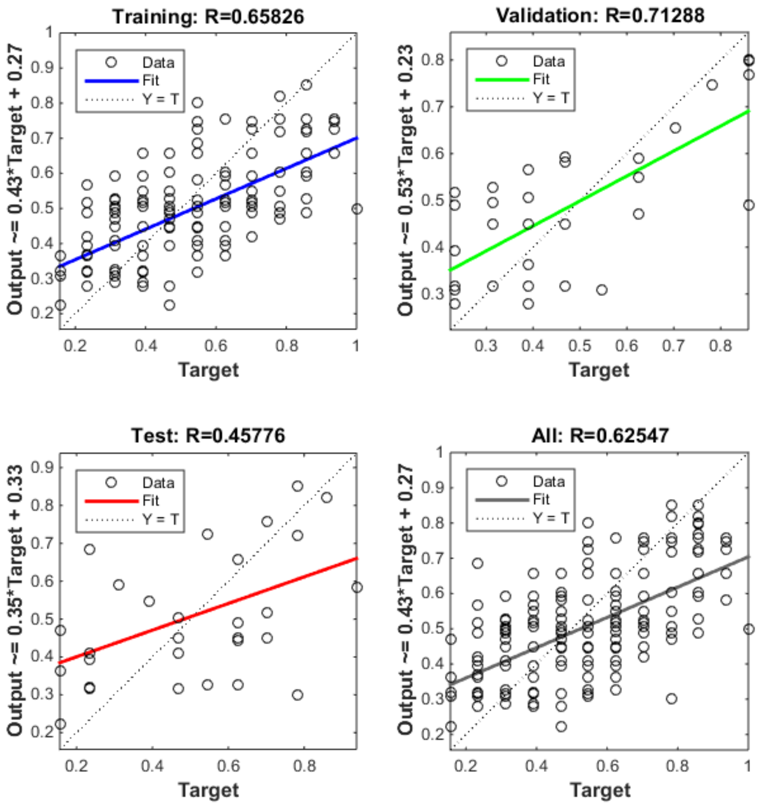


Model 8

Model 8

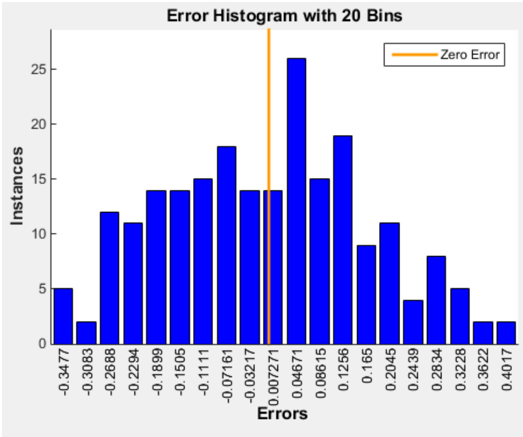


Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.5406
-0.4814
-0.4222
-0.363
-0.3038
-0.2446
-0.1853
-0.1261
-0.06692
-0.00771
0.0515
0.1107
0.1699
0.2291
0.2884
0.3476
0.4068
0.466
0.5252
0.5844

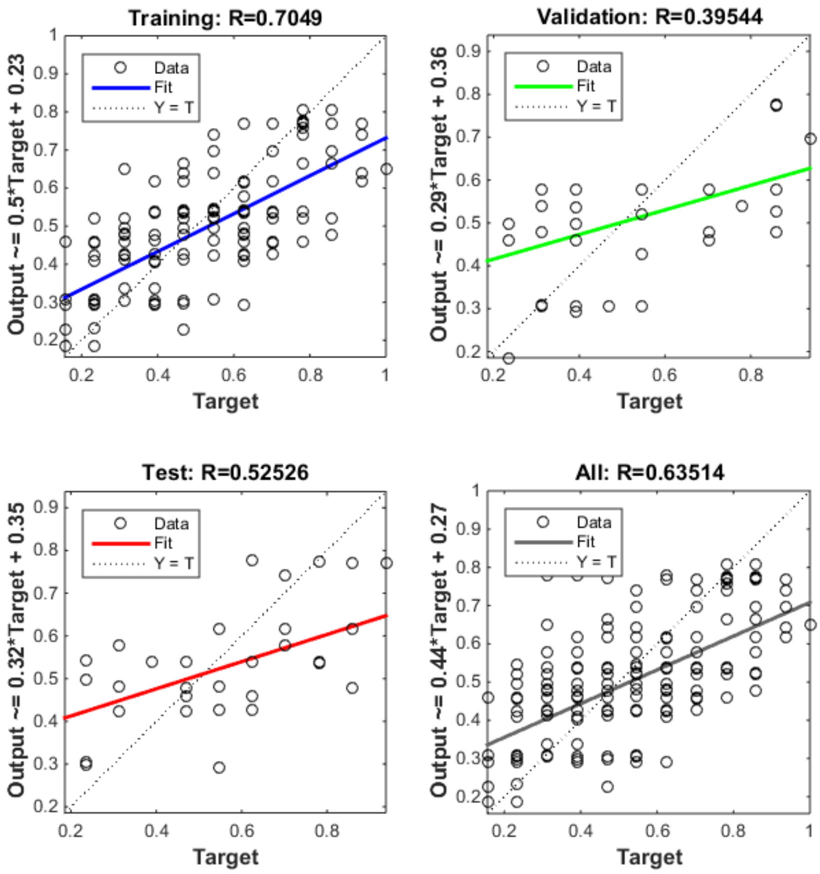


Training: R=0.65826
Output ~= 0.43*Target + 0.27
Validation: R=0.71288
Output ~= 0.53*Target + 0.23
Test: R=0.45776
Output ~= 0.35*Target + 0.33
All: R=0.62547
Output ~= 0.43*Target + 0.27
Data
Fit
Y = T
Target

Model 9

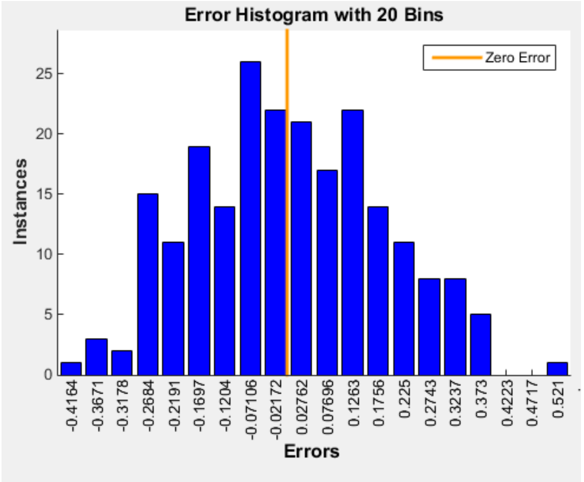


Error Histogram with 20 Bins
Zero Error
Instances
Errors

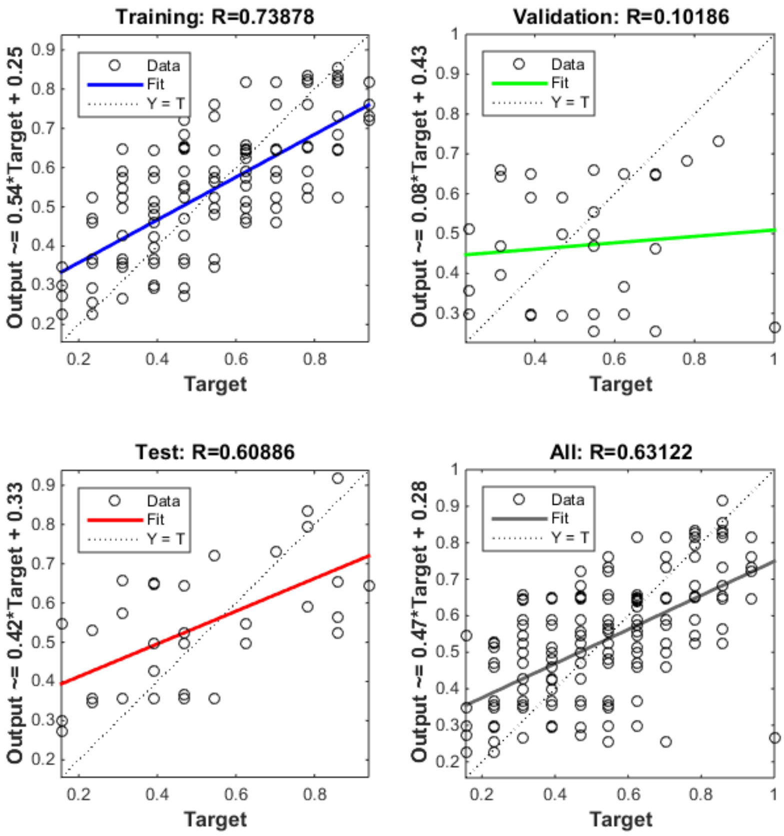


Training: R=0.7049
Output ~= 0.5*Target + 0.23
Validation: R=0.39544
Output ~= 0.29*Target + 0.36
Test: R=0.52526
Output ~= 0.32*Target + 0.35
All: R=0.63514
Output ~= 0.44*Target + 0.27
Data
Fit
Y = T
Target

Model 10

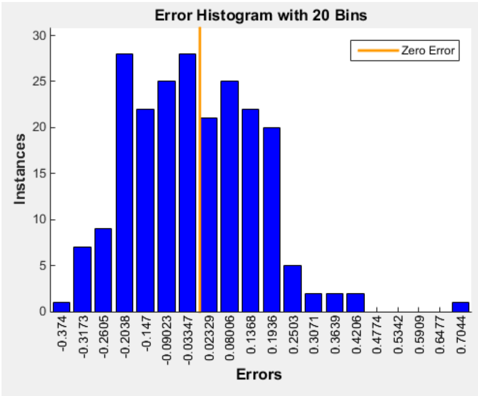


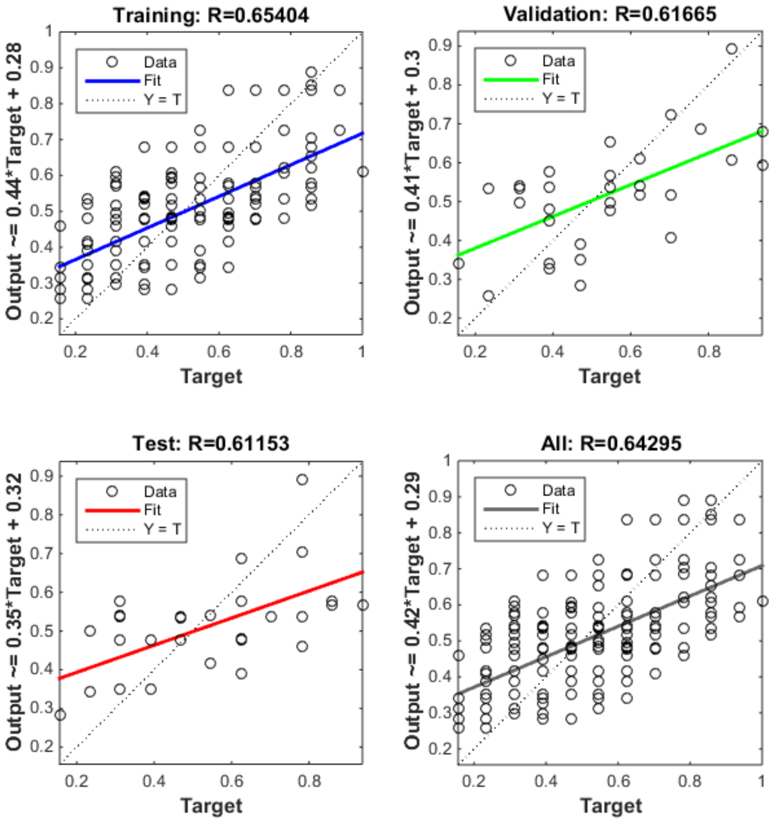
Error Histogram with 20 Bins
Zero Error
Instances
Errors



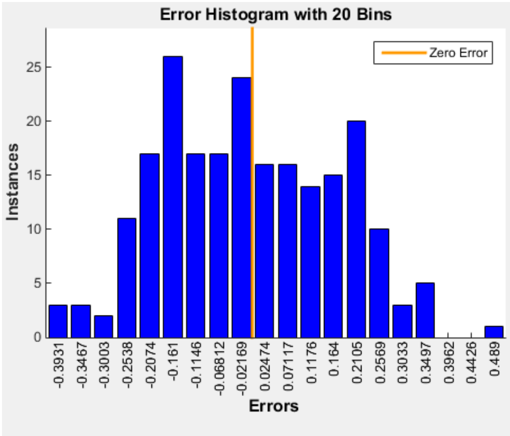
Training: R=0.73878
Output ~= 0.54*Target + 0.25
Validation: R=0.10186
Output ~= 0.08*Target + 0.43
Test: R=0.60886
Output ~= 0.42*Target + 0.33
All: R=0.63122
Output ~= 0.47*Target + 0.28
Data
Fit
Y = T
Target

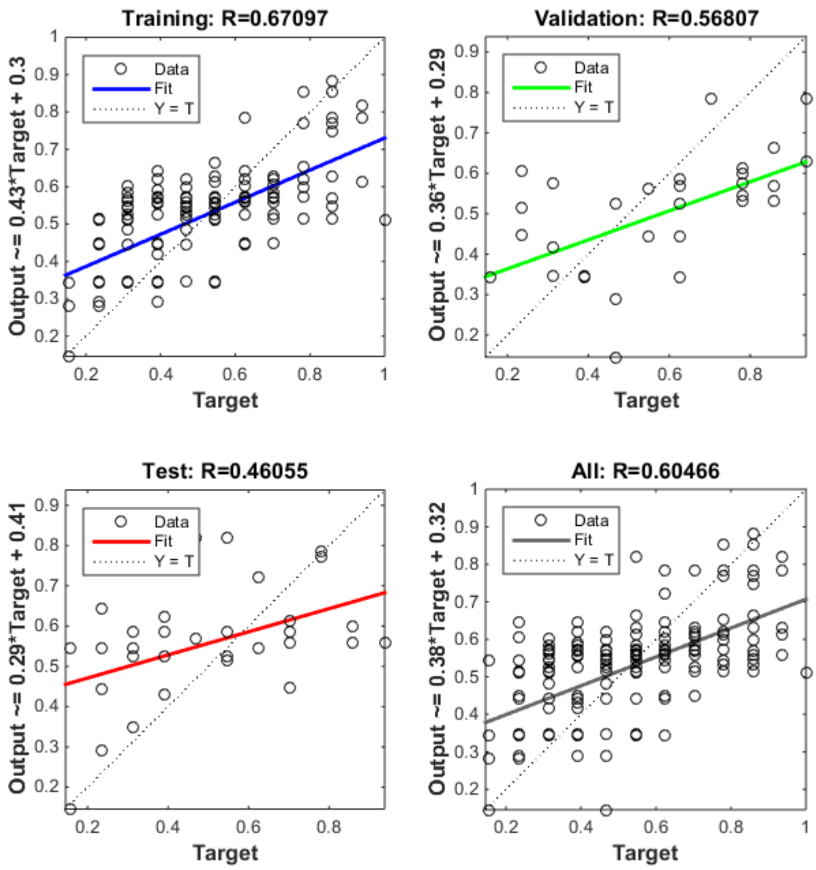
Model 11


Error Histogram with 20 Bins
Zero Error
Instances
Errors

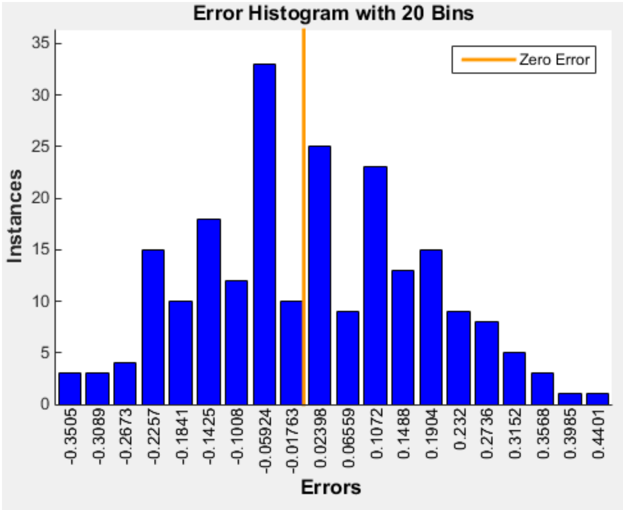

Training: R=0.65404
Output ~= 0.44*Target + 0.28
Validation: R=0.61665
Output ~= 0.41*Target + 0.3
Test: R=0.61153
Output ~= 0.35*Target + 0.32
All: R=0.64295
Output ~= 0.42*Target + 0.29
Data
Fit
Y = T
Target

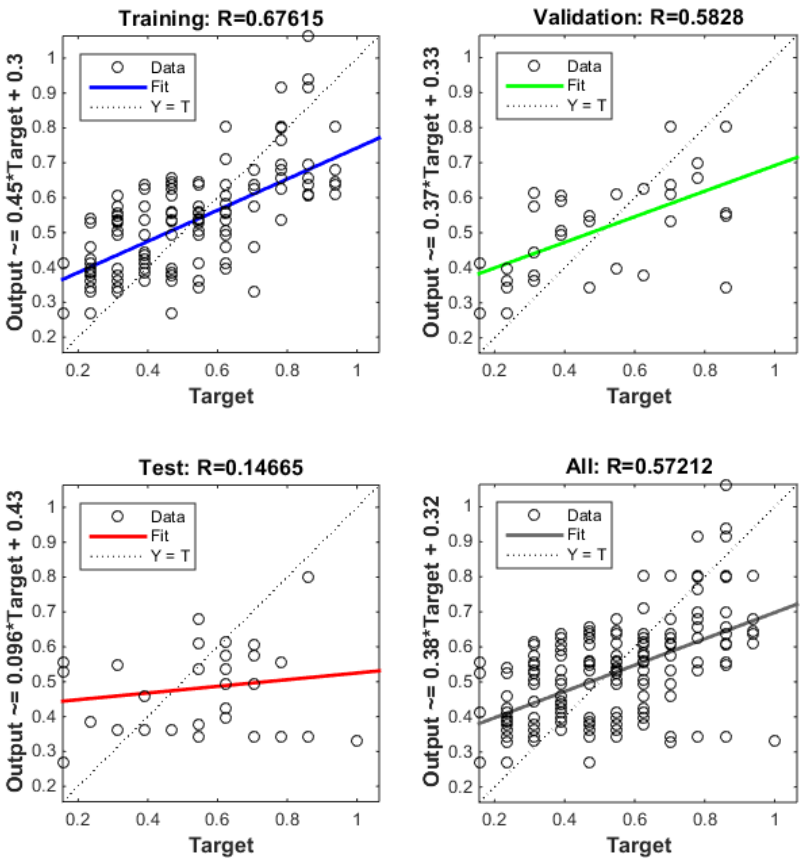
Model 12


Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.3931
-0.3467
-0.3003
-0.2538
-0.2074
-0.161
-0.1146
-0.06812
-0.02169
0.02474
0.07117
0.1176
0.164
0.2105
0.2569
0.3033
0.3497
0.3962
0.4426
0.489

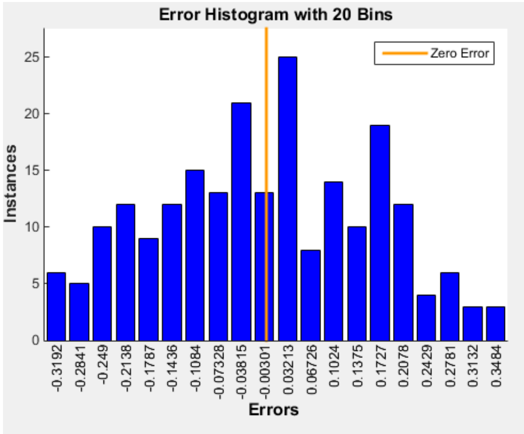

Training: R=0.67097
Output ~= 0.43*Target + 0.3
Validation: R=0.56807
Output ~= 0.36*Target + 0.29
Test: R=0.46055
Output ~= 0.29*Target + 0.41
All: R=0.60466
Output ~= 0.38*Target + 0.32
Data
Fit
Y = T
Target

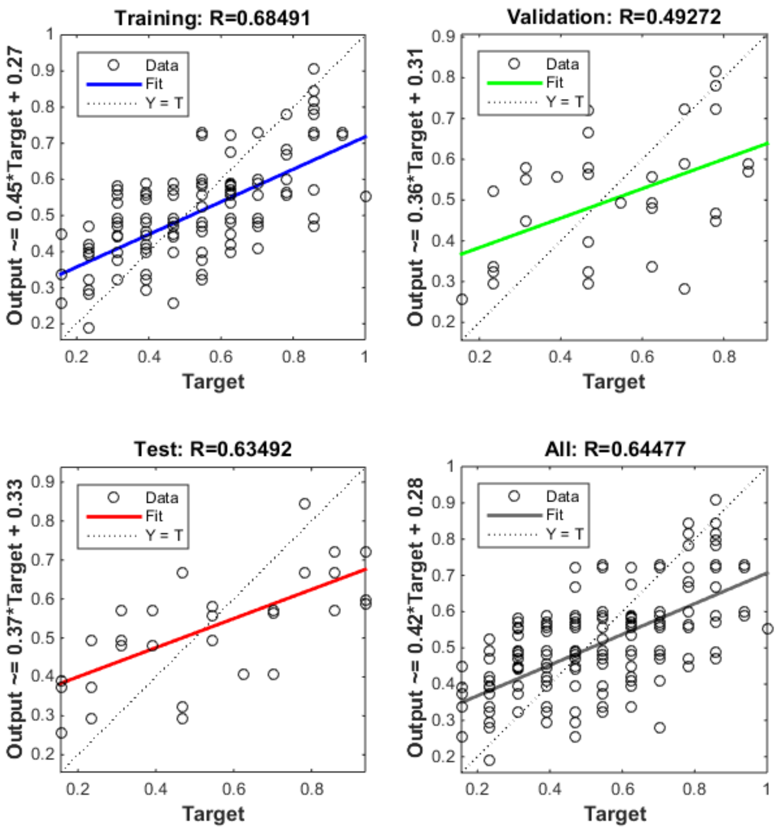
Model 13


Error Histogram with 20 Bins
Zero Error
Instances
Errors
35
30
25
20
15
10
5
0
-0.3505
-0.3089
-0.2673
-0.2257
-0.1841
-0.1425
-0.1008
-0.05924
-0.01763
0.02398
0.06559
0.1072
0.1488
0.1904
0.232
0.2736
0.3152
0.3568
0.3985
0.4401

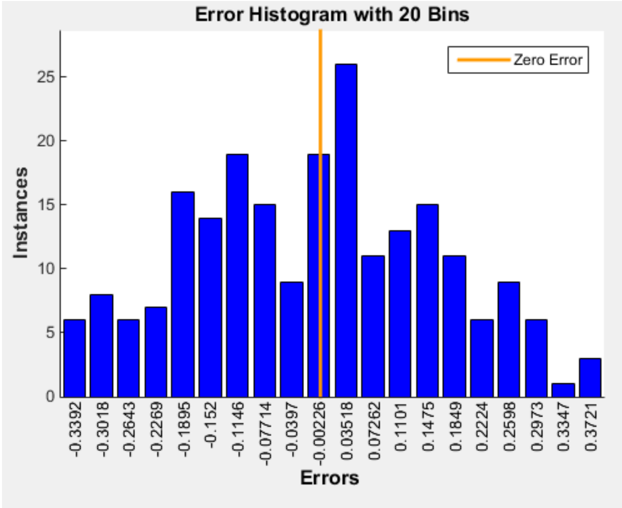

Training: R=0.67615
Output ~= 0.45*Target + 0.3
Validation: R=0.5828
Output ~= 0.37*Target + 0.33
Test: R=0.14665
Output ~= 0.096*Target + 0.43
All: R=0.57212
Output ~= 0.38*Target + 0.32
Data
Fit
Y = T
Target

Model 14

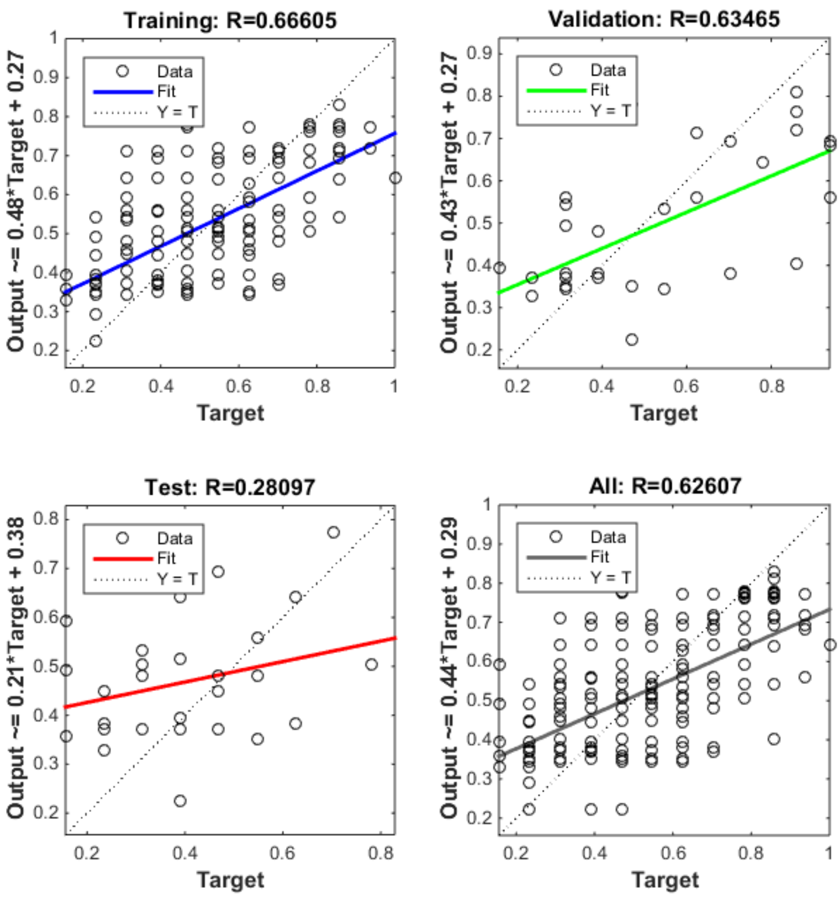

Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.3192
-0.2841
-0.249
-0.2138
-0.1787
-0.1436
-0.1084
-0.07328
-0.03815
-0.00301
0.03213
0.06726
0.1024
0.1375
0.1727
0.2078
0.2429
0.2781
0.3132
0.3484


Training: R=0.68491
Output ~= 0.45*Target + 0.27
Validation: R=0.49272
Output ~= 0.36*Target + 0.31
Test: R=0.63492
Output ~= 0.37*Target + 0.33
All: R=0.64477
Output ~= 0.42*Target + 0.28
Data
Fit
Y = T
Target

Model 15

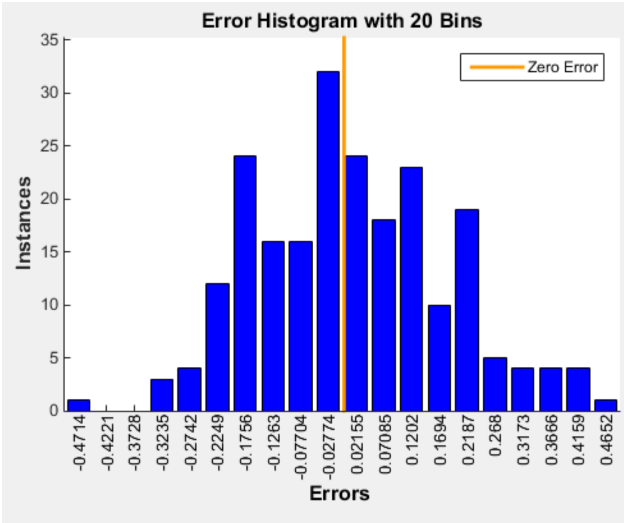


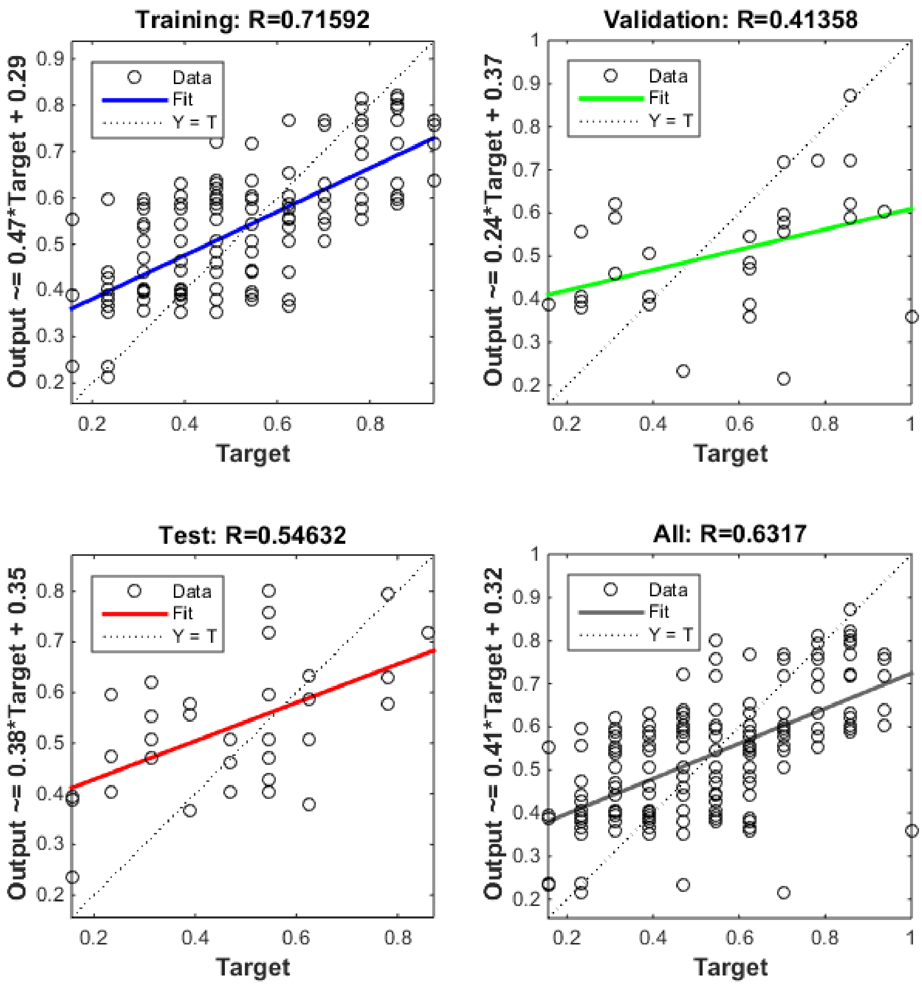
Error Histogram with 20 Bins
Zero Error
Instances
25
20
15
10
5
0
-0.3392
-0.3018
-0.2643
-0.2269
-0.1895
-0.152
-0.1146
-0.07714
-0.0397
-0.00226
0.03518
0.07262
0.1101
0.1475
0.1849
0.2224
0.2598
0.2973
0.3347
0.3721
Errors



Training: R=0.66605
Output ~= 0.48*Target + 0.27
Data
Fit
Y = T
Target
Validation: R=0.63465
Output ~= 0.43*Target + 0.27
Data
Fit
Y = T
Target
Test: R=0.28097
Output ~= 0.21*Target + 0.38
Data
Fit
Y = T
Target
All: R=0.62607
Output ~= 0.44*Target + 0.29
Data
Fit
Y = T
Target

Model 16


Error Histogram with 20 Bins
Zero Error
Instances
Errors
-0.4714
-0.4221
-0.3728
-0.3235
-0.2742
-0.2249
-0.1756
-0.1263
-0.07704
-0.02774
0.02155
0.07085
0.1202
0.1694
0.2187
0.268
0.3173
0.3666
0.4159
0.4652


Training: R=0.71592
Output ~= 0.47*Target + 0.29
Validation: R=0.41358
Output ~= 0.24*Target + 0.37
Test: R=0.54632
Output ~= 0.38*Target + 0.35
All: R=0.6317
Output ~= 0.41*Target + 0.32
Data
Fit
Y = T
Target

Appendix C

General Linear Model: MSE versus Learning Algorithm, ... sfer Function

Method

Factor coding	(-1, 0, +1)

Factor Information

Factor	Type	Levels	Values
Learning Algorithm	Fixed	2	GDX, TrainLm
Hidden layer	Fixed	2	1, 2
H-Neurons	Fixed	2	10, 20
Transfer Function	Fixed	2	Purelin, Tansig

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Learning Algorithm	1	0.000107	0.000107	2.01	0.164
Hidden layer	1	0.000151	0.000151	2.83	0.101
H-Neurons	1	0.000574	0.000574	10.80	0.002
Transfer Function	1	0.000097	0.000097	1.82	0.186
Learning Algorithm*Hidden layer	1	0.000001	0.000001	0.02	0.879
Learning Algorithm*H-Neurons	1	0.000018	0.000018	0.33	0.568
Learning Algorithm*Transfer Function	1	0.000009	0.000009	0.16	0.691
Hidden layer*H-Neurons	1	0.000108	0.000108	2.02	0.163
Hidden layer*Transfer Function	1	0.000346	0.000346	6.51	0.015
H-Neurons*Transfer Function	1	0.000010	0.000010	0.19	0.669
Error	37	0.001967	0.000053		
Lack-of-Fit	5	0.000123	0.000025	0.43	0.827
Pure Error	32	0.001844	0.000058		
Total	47	0.003386			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0072911	41.91%	26.21%	2.24%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.03715	0.00105	35.30	0.000	
Learning Algorithm					
GDX	-0.00149	0.00105	-1.42	0.164	1.00
Hidden layer					
1	-0.00177	0.00105	-1.68	0.101	1.00
H-Neurons					
10	-0.00346	0.00105	-3.29	0.002	1.00
Transfer Function					
Purelin	-0.00142	0.00105	-1.35	0.186	1.00
Learning Algorithm*Hidden layer					
GDX 1	-0.00016	0.00105	-0.15	0.879	1.00
Learning Algorithm*H-Neurons					
GDX 10	0.00061	0.00105	0.58	0.568	1.00
Learning Algorithm*Transfer Function					
GDX Purelin	0.00042	0.00105	0.40	0.691	1.00
Hidden layer*H-Neurons					
1 10	0.00150	0.00105	1.42	0.163	1.00
Hidden layer*Transfer Function					
1 Purelin	-0.00269	0.00105	-2.55	0.015	1.00
H-Neurons*Transfer Function					
10 Purelin	0.00045	0.00105	0.43	0.669	1.00

Regression Equation

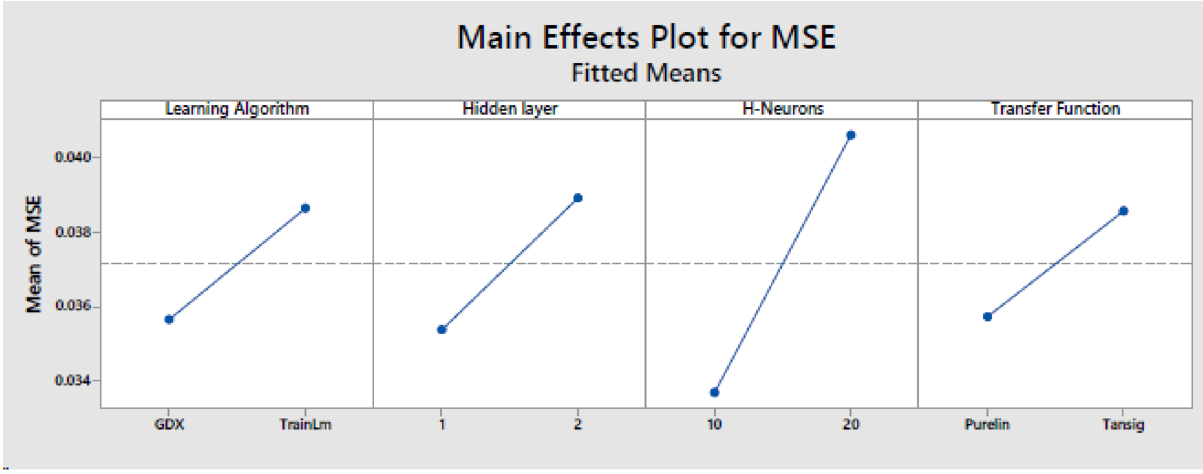
MSE = 0.03715 - 0.00149 Learning Algorithm_GDX + 0.00149 Learning Algorithm_TrainLm
- 0.00177 Hidden layer_1 + 0.00177 Hidden layer_2 - 0.00346 H-Neurons_10
+ 0.00346 H-Neurons_20 - 0.00142 Transfer Function_Purelin
+ 0.00142 Transfer Function_Tansig - 0.00016 Learning Algorithm*Hidden layer_GDX 1
+ 0.00016 Learning Algorithm*Hidden layer_GDX 2
+ 0.00016 Learning Algorithm*Hidden layer_TrainLm 1
- 0.00016 Learning Algorithm*Hidden layer_TrainLm 2
+ 0.00061 Learning Algorithm*H-Neurons_GDX 10
- 0.00061 Learning Algorithm*H-Neurons_GDX 20
- 0.00061 Learning Algorithm*H-Neurons_TrainLm 10
+ 0.00061 Learning Algorithm*H-Neurons_TrainLm 20
+ 0.00042 Learning Algorithm*Transfer Function_GDX Purelin
- 0.00042 Learning Algorithm*Transfer Function_GDX Tansig
- 0.00042 Learning Algorithm*Transfer Function_TrainLm Purelin
+ 0.00042 Learning Algorithm*Transfer Function_TrainLm Tansig
+ 0.00150 Hidden layer*H-Neurons_1 10 - 0.00150 Hidden layer*H-Neurons_1 20
- 0.00150 Hidden layer*H-Neurons_2 10 + 0.00150 Hidden layer*H-Neurons_2 20
- 0.00269 Hidden layer*Transfer Function_1 Purelin

+ 0.00269 Hidden layer*Transfer Function_1 Tansig
+ 0.00269 Hidden layer*Transfer Function_2 Purelin
- 0.00269 Hidden layer*Transfer Function_2 Tansig
+ 0.00045 H-Neurons*Transfer Function_10 Purelin
- 0.00045 H-Neurons*Transfer Function_10 Tansig
- 0.00045 H-Neurons*Transfer Function_20 Purelin
+ 0.00045 H-Neurons*Transfer Function_20 Tansig

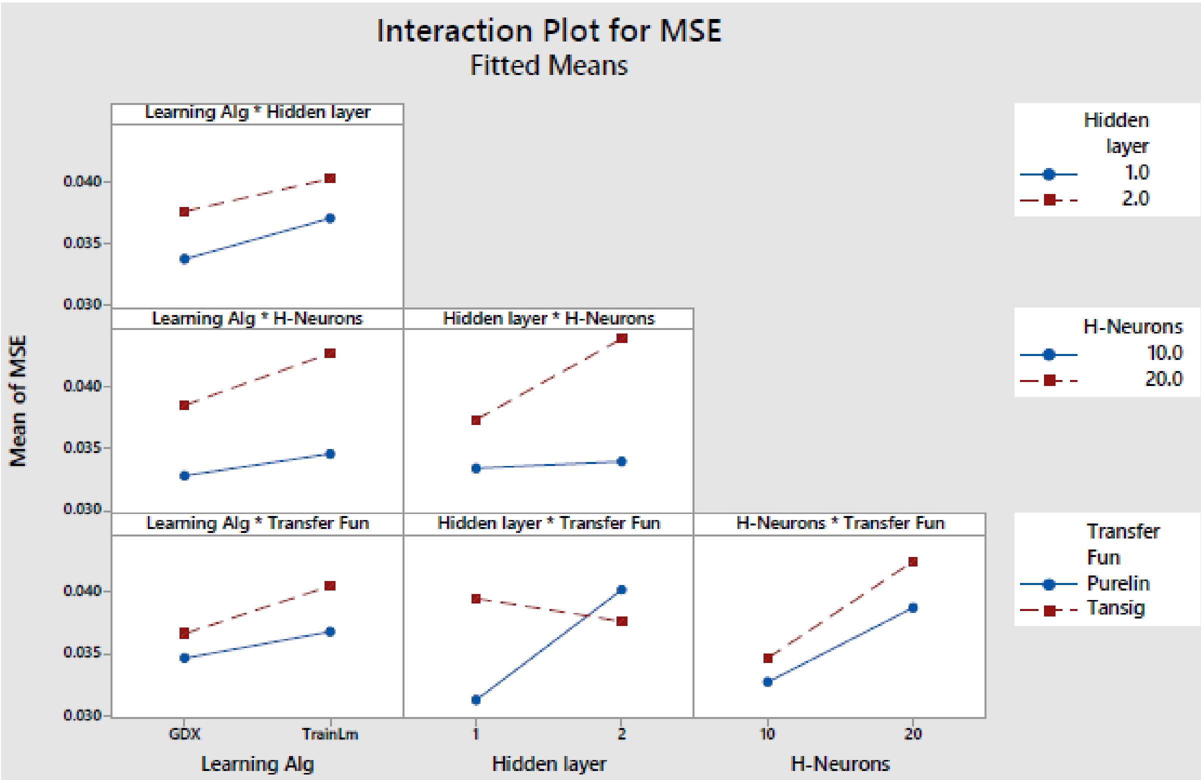
Fits and Diagnostics for Unusual Observations

Obs	MSE	Fit	Resid	Std Resid	
4	0.04865	0.03339	0.01526	2.38	R
10	0.05470	0.04070	0.01400	2.19	R
39	0.03261	0.04621	-0.01359	-2.12	R

R Large residual



Main Effects Plot for MSE
Fitted Means
Learning Algorithm
Hidden layer
H-Neurons
Transfer Function
Mean of MSE
0.040
0.038
0.036
0.034
GDX
TrainLm
1
2
10
20
Purelin
Tansig



Interaction Plot for MSE
Fitted Means
Learning Alg * Hidden layer
Learning Alg * H-Neurons
Hidden layer * H-Neurons
Learning Alg * Transfer Fun
Hidden layer * Transfer Fun
H-Neurons * Transfer Fun
Mean of MSE
0.040
0.035
0.030
Hidden layer
1.0
2.0
H-Neurons
10.0
20.0
Transfer Fun
Purelin
Tansig
GDX
TrainLm
1
2
10
20
Learning Alg
Hidden layer
H-Neurons