MODELLING OF VISCOELASTIC PROPERTIES OF MODIFIED ASPHALT CEMENT

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Yassin ABDULHADI: MODELING OF VISCOELASTIC PROPERTIES OF MODIFIED ASPHALT CEMENT

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ABSTRACT

The performance of bituminous pavement is dependent on the physical and rheological characteristics of asphalt binders, which are strongly influenced by the loads imposed by vehicular traffic and climatic conditions. In this study, six different blends including base binder, polymer modified binder (%5 ASA by the weight of bitumen), and two different polymer nanocomposite materials, ASA-Nano calcium and ASA-Nano copper at 3% and 5% concentrations by the weight of bitumen, were characterized for rheological properties using a dynamic shear rheometer (DSR). Complex shear modulus (G*) and phase angle (δ) were the two parameters revealed in the DSR oscillation tests. within the scope of this research, prediction of G* from physical and rheological properties of binders and the mechanical test conditions were performed using analytical approaches, namely an artificial neural network (ANN) and an adaptive neuro-fuzzy inference system (ANFIS). Coefficient of determination (R^2) and root mean squared error (RMSE) was used as the performance indicator metrics in the evaluation of the performance of the analytical models. The results of this study demonstrated that polymer and polymer nanocomposite material modification enhanced the rheological behaviour of the asphalt binder. Furthermore, the ANN and ANFIS models for predicting the outcomes of the DSR test results have been shown to be reliable with both training and testing datasets. An R^2 value of 0.9960 and an RMSE value of 0.008295 were observed for the testing dataset, which indicated that both ANN and ANFIS models were able to predict G* with high accuracy, with ANN being the analytical model with the more efficient performance.

Keywords**:** Dynamic Shear Rheometer; Polymer Modified Bitumen; Polymer Nanocomposite; Artificial Neural Network; Adaptive Neuro-Fuzzy Inference System

ÖZET

Bitümlü kaplamaların performansı, taşıt trafiği ve iklim koşulları tarafından uygulanan yüklerden kuvvetli bir şekilde etkilenen asfalt bağlayıcıların fiziksel ve reolojik özelliklerine bağlıdır. Bu çalışmada, baz bağlayıcı, polimer modifiyeli bağlayıcı (bitüm ağırlığına göre% 5 ASA) ve iki farklı polimer nanokompozit malzeme, ASA-Nano kalsiyum ve ASA-Nano bakır dahil olmak üzere altı farklı karışım; bitümün ağırlığı, dinamik kesme reometresi (DSR) kullanarak reolojik özellikler için karakterize edildi. Kompleks kayma modülü (G *) ve faz açısı (δ) DSR salınım testlerinden seçildi. Modifiye edilmiş bağlayıcıların viskoelastik özelliklerinin ve mekanik test koşullarının tahmini, daha önce yapay bir sinir ağı (ANN) ve adaptif bir nöro-bulanık çıkarım sistemi (ANFIS) olan analitik yaklaşımlar kullanılarak gerçekleştirildi. Analitik modellerin performansının değerlendirilmesinde belirleme katsayısı (R^2) ve kök ortalama kare hatası (RMSE) performans gösterge ölçütleri olarak kullanılmıştır. Bu çalışmanın sonuçları, polimer ve polimer nanokompozit malzeme modifikasyonunun, asfalt bağlayıcı maddenin reolojik davranışını arttırdığını göstermiştir. Ayrıca, DSR test sonuçlarının sonuçlarını tahmin etmeye yönelik ANN ve ANFIS modellerinin hem eğitim hem de test veri setleri için güvenilir olduğu gösterilmiştir. Test veri seti için 0.9960'lık bir R2 değeri ve 0.008295'lik bir RMSE değeri gözlendi, bu hem ANN hem de ANFIS modellerinin G* 'yi yüksek doğrulukla tahmin edebildiğini gösterdi, ANN daha verimli performansa sahip analitik modeldir.

Anahtar kelimeler : Dinamik Kesme Reometresi; Polimer Modifiyeli Bitüm; Polimer Nanokompozit; Artificial Neural Network; Adaptive Neuro-Fuzzy Inference System

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LIST OF ABBREVIATIONS

AC:	Asphalt concrete
AI:	Artificial Intelligence
ANFINS:	Adaptive Neuro-Fuzzy Inference System
ANN:	Artificial Neural Network
ANN:	Artificial Neural Network
ASTM D36:	Standard Test Method for Softening Point of Bitumen
ASTM D5:	Standard Test Method for Penetration of Bituminous Materials
ASTM D4957:	Standard Test Method for Apparent Viscosity of Asphalt Emulsion Residues and Non-Newtonian Asphalts by Vacuum Capillary Viscometer
BBR:	Bending Beam Rheometer
EVA:	Ethylene-vinyl acetate
GEP:	Gene Expression Program
GP:	Genetic programming
DII:	Direct Tension
DSR:	Dynamic Shear Rheometer
G*:	Dynamic shear modulus
HSC:	High-strength concrete

MILP Multilayer Perceptron Neural Network

NSC: Normal Strength

NR Natural rubber

PAV: Pressure Aging Vessel

δ: Phase Angle

PMAC: polymer modified asphalt cement

RBFN: Radial Network

RNN: Recurrent Neural Network

RTFO: Rolling Thin Film Oven

SVM: Support Vector Machine

PP: Polypropylene

CHAPTER 1
INTRODUCTION

1.1 Introduction

Bitumen is, a dark brown colored hydrocarbon obtained as a byproduct of distillation of crude oil, is mostly used in pavement construction due to its viscoelastic and adhesive properties, (Kok, Yilmaz, Sengoz, Sengur, & Avci, 2010),Bitumen is made of complex mixtures of aromatic, aliphatic and naphthenic hydrocarbons with a small amount of metallorganic and other organic (Yilmaz, Kok, Sengoz, Sengur, & Avci, 2011). Bitumen can be considered as one of the oldest engineering materials in the world, have been used since the beginning of civilization in many different fields, for example in electrical industry by mixing the high-grade Bitumen with wood tar, pitch, rubber, and resin, also in construction field in roll roofing , bridges, dams, and reservoirs because it helps to preserve and waterproof (Speight, 2015), and as mentioned in previous it is widely used in pavement construction it is preferred choice due to the smooth surface which provides to the road, therefore it increases the safety for driver, and more economy by reducing the rolling resistance, which means better fuel economy and it reduce carbon dioxide emissions which means for the environment more friendly (West & MADISON, 2005).

Bitumen is highly temperature susceptible which means its physical and chemical properties change when subjected to various temperature conditions (Kim, 2008). Also, viscoelastic materials such as Bitumen do not behave linearly, in terms of their stiffness, as a function of stress or strain (Yusoff, Breem, Alattug, Hamim, & Ahmad, 2014). In performance grading specifications Bitumen is characterized by its physical and the above-mentioned rheological properties.

There are different types of tests must be conducted to the asphalt binders in order to find out the properties of it. It can be classified as: Direct Tension (DTT), Bending Beam Rheometer (BBR), Rolling Thin Film Oven (RTFO), Pressure Aging Vessel (PAV), Absolute Viscosity, Kinematic Viscosity, Apparent Viscosity of Non-Newtonian Bitumen (ASTM D4957), Rotational Viscosity, Penetration, Specific Gravity, Softening Point, Flash Point, Solubility (ASTM D2042), Ductility, Elastic Recovery, Force Ductility, Screen Test, Thin Film Oven, Separation, and Dynamic Shear Rheometer (DSR).

Dynamic Shear Rheometer (DSR) is used in the assessment of rheological properties of asphalt binders at intermediate and high temperatures. Dynamic shear modulus (G*) which is considered as the material's resistance to deformation under repeated shear loading and the phase angle (δ) which is defined as the lag between the applied shear stress and the resulting shear strain are the two parameters revealed upon oscillatory shear testing performed by (Abedali, 2015). These parameters are further used in the assessment of rutting and fatigue resistance which are the most common modes of failures in asphalt pavement. It is favorable that, asphalt binders demonstrate stiff behavior at high temperatures and low frequencies and elastic behavior at low temperatures and high frequencies in order to prevent rutting and fatigue failures (Bala, Napiah, & Kamaruddin, 2018).

Due to the limitations of Bitumen regarding the temperatures, various types of modifiers such as plastic, polymers, and Nano-materials were added to the base asphalt to improve the performance of the asphalt mixture (Cuadri, Partal, Navarro, García-Morales, & Gallegos, 2011b), therefore in order to improve rheological properties, asphalt modification with polymeric materials is a common practice and referred to as polymer modified asphalt cement (PMAC). An advantage of PMAC is that they are available and research and field tested (Ezzat, El-Badawy, Gabr, Zaki, & Breakah, 2016). Polymers can be sub-grouped as elastomers and plastomers. Elastomers are favorable modifiers of AC at low temperatures, where plastomers are more suitable modifiers at high temperatures (Zhu, Birgisson, & Kringos, 2014). The polymer which used as a modifier for Bitumen is consist of Styrene-Butadiene-Styrene (SBS), Ethylene-vinyl acetate (EVA), Natural rubber (NR) and Polypropylene (PP) (Al-Mansob et al., 2014; Habib, Kamaruddin, Napiah, & Isa, 2011; Sengoz & Isikyakar, 2008; Yildirim, 2007).

On the other hand, polymers are expensive and some of them have proven to have an insignificant improvement in the performance of AC due to the incompatibility of polymer with the base binder (Golestani, Nam, Nejad, & Fallah, 2015). Due to shortcomings of PMACs, nanomaterials have been introduced as an alternative to polymer modified bitumen. Unique properties of nanomaterials such as high surface work, a large fraction of surface atoms, structural features, quantum effects, and spatial confinement are some of the features that promote the improvement of binder properties in terms of stiffness and also leads to higher temperature susceptibility and improved strength of bitumen against moisture damage (Saltan, Terzi, & Karahancer, 2018). Nanomaterials have also shown to enhance the incompatibility problem of polymer and Bitumen, associated with the occurrence of phase separation. Common nanomaterials used in this purpose include nano silica, nanoclay and carbon nanotubes (Ezzat et al., 2016; Yang & Tighe, 2013; Ziari, Amini, Goli, & Mirzaeiyan, 2018). According to previous studies in the literature, enhancement in the performance of bitumen modified with nanomaterials in terms of improved complex modulus and reduced phase angle have indicated that better rutting resistance performance is achieved (Xiao, Amirkhanian, & Amirkhanian, 2010) However, the field of nanomaterial in the bitumen modification still requires a significant amount of research before field application.

Laboratory experimentation of AC is time and resource intensive process. Therefore many researchers have attempted to develop mathematical and computational models to predict performance characteristics of AC in order to assist with the experimental procedures (Venudharan & Biligiri, 2017). As acknowledged in the literature, the physical and chemical properties of asphalt binders have a strong influence on the performance characteristics of AC. However, the relationship was not in high correlation. Rather, test conditions such as temperature and frequency were highly correlated with the performance characteristics (Ali et al., 2017; Venudharan & Biligiri, 2017).

By a review for a recent works it can be noticed that an increasing trend of applying artificial intelligence (AI) method including Artificial Neural Network (ANN), Multilayer Perceptron Neural Network (MILP), Genetic programming (GP), Radial Network (RBFN), Support Vector Machine (SVM), Gene Expression Program (GEP), Recurrent Neural Network (RNN) networks, and Adaptive Neuro-Fuzzy Inference System (ANFIS) consolidating the accuracy and productivity of the required task in the pavement field.

Performance of nanomaterial modified bitumen have also been acknowledged in the literature by a limited number of studies (Firouzinia & Shafabakhsh, 2018; Ziari et al., 2018). However, asphalt binders modified with polymer nanocomposite materials have been only limited to be addressed by experimental investigations and tangibility of ANN and ANFIS modeling in this matter requires further study. Therefore this basis computational models, Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were implemented in this study using physical properties of, bitumen modified with polymer and polymer nanocomposites at various concentrations and test conditions as predictor and the performance characteristics indicator, complex modulus (G*) as the predicted variable.

ANN is a black box framework inspired by the way biological neurons work. ANN models have the ability to solve problems by applying information gained from past experience to new problems or case scenarios (Dasgupta, 1993). ANN has been previously used in the modeling of some significant parameters of pavement materials with the purpose of obtaining reliable analytical solutions to assist in experimental investigations. Complexity in the behavior of pavement materials are further escalated with the use of modified binders and on this basis, ANN, a nonlinear nonparametric modeling technique that offers a high degree of accuracy to solve complex nonlinear relationship problems has been gaining the attention of researchers in the field of material science and pavement engineering. Some studies devoted to ANN modeling of polymer modified binders include (Golzar, Jalali-Arani, & Nematollahi, 2012; Specht, Khatchatourian, Brito, & Ceratti, 2007; Tapkın, Çevik, & Uşar, 2009).

ANFIS is another type of Artificial Intelligence approach to analytical modeling of bituminous binders which represents the incorporation of the artificial neural network and fuzzy logic knowledge (Mohammadi et al., 2015). ANFIS has been used widely in the prediction process due to its capabilities to deal with complex nonlinear problems in a professional way (Parmar & Bhardwaj, 2015). The system of fuzzy modeling, invented by Takagi and Sugeno in 1985, also found numerous practical applications in control (Sugeno 1985, Pedrycz 1989), prediction and inference (Kandel1988,1992). ANFIS was announced as a new approximator system which represents highly nonlinear functions by Jang and Jangetal (Jang, Sun, Mizutani, & Ho, 1998), Many researchers have been used ANFIS in the pavement field due to its adaptability and computational efficiency to deal with Complex behavior of pavement materials.

1.2 Problem Statement

In the field of pavement construction, to improve the quality of asphalt mixture varies modifiers like polymers and nano-materials were used. Due to the high cost of some materials and leakage in laboratory equipment which has a high cost as well. That leads to a limited number of studies that have been acknowledging the performance of modified bitumen with nanomaterial (Firouzinia & Shafabakhsh, 2018; Ziari et al., 2018). It can be noticed that the field of nanomaterial in the bitumen modification still requires significant amount of research before field application, while most of the studies which have been done to asphalt binders modified with polymer nanocomposite materials are limited to be addressed by experimental investigations and tangibility of ANN and ANFIS modelling in this matter requires further study. Therefore, Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were implemented in this study using physical properties of, bitumen modified with polymer and polymer nanocomposites at various concentrations and test conditions as predictor and the performance characteristics indicator, complex modulus (G*) as the target variable to find out the behavior of Bitumen modified with polymer and polymer nanocomposite materials.

1.3 The Objective of the Study

The objectives of the study are to:

- To undertake a literature review which discusses and analyses the application of Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in the field of pavement design.

- To develop the ANN and ANFIS model to predict the viscoelastic properties of modified asphalt cement.

- To establish a comparison study between the Artificial Neural Networks (ANN) modeling, Adaptive Neuro-Fuzzy Inference System (ANFIS) modeling and the experimental results.

1.4 Significant of Study

Due to the leakage of the studies that have been discussed the performance of modified bitumen with nanomaterial and the studies which have been conducted to asphalt binders modified with polymer nanocomposite materials are limited to be addressed only by experimental test therefore the results of the study will be of great benefit to the pavement field by finding the viscoelastic properties of modified asphalt cement at elevated temperatures and frequencies using Artificial Neural Network (ANN) model and Adaptive Neuro-Fuzzy Inference System (ANFIS) model in the prediction process and showing the capability and efficiency of this applications to deal with Complex behavior of pavement materials.

1.5 Thesis Organization

chapter one is explaining the introduction about the topic, problems statement, and objective of the study while chapter two is addressing the previous studies carried on or related to the study area. In addition, chapter three is providing in detail the methods and procedures that carried on to achieve the objectives of the study and chapter for discusses the results of the research while chapter five is about the conclusion.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Bituminous materials are hydrocarbon which obtained as a product of the distillation of crude petroleum or found in natural deposits (Read & Whiteoak, 2003). All bituminous materials consist primarily of bitumen and have strong adhesive properties, it has the capacity adhere to a solid surface in a fluid stat depending on the surface's nature, while the adhesion could be prevented by adding water to surface, therefore the Bitumen is water resistant, the flow or viscous properties of bitumen change according to stress and temperature conditions. The failure, or loss of the desirable properties of bitumen, can be noticed it takes the form of hardening. Resultantly, a decrease in flow and adhesive properties and an increase in the coefficient of thermal expansion and the softening point temperature (Mochinaga et al., 2006). All bituminous materials have colors ranging from dark brown to black. Also, asphalts are thermoplastic materials, meaning that they liquefy when heated and solidify when cooled (Ali et al., 2017).

To check the efficiency of the Asphalt in the site, designing the physical properties of the binders is very fundamental. There to find out the properties of Asphalt the following testing methods are carried out: Direct Tension (DTT), Bending Beam Rheometer (BBR), Rolling Thin Film Oven (RTFO), Pressure Aging Vessel (PAV), Absolute Viscosity, Absolute Viscosity, Kinematic Viscosity, Apparent Viscosity of Non-Newtonian Bitumen (ASTM D4957), Rotational Viscosity, Penetration, Specific Gravity, Softening Point, Flash Point, Solubility (ASTM D2042), Ductility, Elastic Recovery, Force Ductility, Screen Test, Thin Film Oven, Separation, and Dynamic Shear Rheometer (DSR).

2.2 Types of Bitumen

Bitumen has been used since the old civilization until now due to its natural resources, it can be used in the different field for humans needs such as waterproofing in sealing flat roofs and roofing felt, while most of the Bitumen produced used in pavement field due to the following reasons (Yildirim, 2007):

- Production of bitumen is economical
- Rheological and Physical Properties of it bring versatility
- Bitumen melts at a low point
- Bitumen can be recycled
- Bitumen increase adhesive nature
- Bitumen has a diversity color

There are different types of Bitumen available with different properties, specifications and uses based on the task. The specification of Bitumen to display the safety, disparity with the durability, physical properties, and the solubility. The Bitumen can be categorized into the following grade types:

2.2.1 Penetration grade bitumen

The penetration grade bitumen is refinery bitumen that is produced at different viscosities. The penetration test is carried out to characterize the bitumen, based on the hardness. Thus, it has the name penetration bitumen. The range of the penetration grades from 15 to 450 at standard test conditions which commonly used for road asphalt. But the most used range is 25 to 200. This is acquired by controlling the test for the distillation procedure. the required hardness can be reached by applying a partial control of fluxing the residual Bitumen with the oils (Read & Whiteoak, 2003).

2.2.2 Oxidized bitumen

The filter bitumen is further managed by inserting the produced air. The way the oxidized bitumen is produced. By preserving an adjusted temperature, the air is inserted under pressure into smooth bitumen. by the reaction of the components of bitumen and this introduced oxygen, a Compounds of higher molecular weight are formed. The Maltenes and the Asphaltenes content helps in increasing the harder mix. The mix which has a temperature sensitivity and a less ductility. This type of Bitumen is commonly used in manufacturing fields such as covering for pipes and ceiling. By this way of producing, the Bitumen which has a less penetration can be produced, it can be used in the pavement (Loeber, Muller, Morel, & Sutton, 1998).

2.2.3 Cutback bitumen

This type is called to the bitumen when it has a grade less than penetration grade, it has a decreased viscosity for a specific time by inserting of volatile oil. the bitumen gain back its normal viscosity when the volatile materials are evaporated after the application. The penetration grade Bitumen can be classified as a thermoplastic material. It demonstrates the various value of viscosity for various temperature. In the site of the road industry, it is requisite for the materials to be a liquid shape in surface dressing phase. By cutback asphalt, the material can earn back its normal rigidity after casting. By increasing the temperature, the liquidity can be for any bitumen. cutback bitumen is used when there is a need to have fluidity for any bitumen at lower temperatures in the surface dressing phase (Lamperti, 2011).

2.2.4 Bitumen emulsion

This kind of bitumen has 2 phase system with 2 immiscible fluids. The first one is scattered like specific globules included in the other fluid. This kind of bitumen is obtained once the separate globules of bitumen are separated from a continuous form of water. An emulsifier having a long hydrocarbon series with an anionic or cationic ending is applied for receding the bitumen globules. This type supplies an electrochemical climate. The ionic section of the series has an attraction to the water and the bitumen is attracted by hydrocarbon section. This bitumen is conducted by using sprays also the viscosity has the main attention. when the content of the bitumen is increased, the viscosity of the mixture increased. The stability of emulsions relies on the Water evaporation rate, the types of bitumen emulsifier and its quantity, the mechanical forces, and the bitumen globules size (Brown & Needham, 2000).

2.3 Pavement distresses

The pavement may face too many distress some of them may occur according to the chemical and physical properties of the asphalt binder, while the other may occur by the weather conditions and the loads which applied by the tracks. The distresses are as the following:

2.3.1 Fatigue

(Alligator) Cracking: is the principal structural distress, the layer materials and thicknesses of pavement, applied loads the consistency of the asphalt cement, the bitumen content and the air voids and aggregate characteristics of the asphalt concrete mix are the factors which affect the development of fatigue(El-Basyouny & Witczak, 2005).

2.3.2 Bleeding

Bleeding is a cumulation of asphalt cement material at the pavement surface, beginning as individual drops which eventually coalesce into a shiny, sticky film. Bleeding decries the surface friction and is, therefore, a potential safety hazard. Bleeding is the result of a mix insufficiency when the asphalt cement content in excess of that which the air voids in the mix can accommodate at higher temperatures when the asphalt cement expands (Xu & Huang, 2012).

2.3.3 Block cracking

Block cracking is a crack of an asphalt pavement which takes a rectangular shape. It is related to the use of an asphalt cement which is or has become too stiff for the climate. Block cracking caused by shrinkage of the asphalt concrete in response to low temperatures, and progress from the surface of the pavement downward (Adlinge & Gupta, 2013).

2.3.4 Frost heave

Frost heave It happens in freezing climates, in frost-susceptible soils when enough water is available. When the temperature in the soil reaches the freezing point, this water freezes and becomes ice lenses, which will be thicker. The progressive growth process of these ice lenses is still continuing as additional water is drawn to the freezing front that produces the dramatic raising of the road surface known as frost heave (Johanneck & Khazanovich, 2010).

2.3.5 Pothole

Pothole: is a bowl-shaped hole through one or more layers of the asphalt pavement structure, between 15 cm to 90 cm in diameter. Potholes start to form when crumbs of asphalt concrete are displaced by traffic wheels, in fatigue-cracked areas. Potholes increase in depth and size as water present in the hole and penetrate into the base and subgrade, which increase weakness in the vicinity of the pothole (Koch, Jog, & Brilakis, 2012).

2.3.6 Raveling

Raveling is occurred by the continued infiltration of water and the break downing of an asphalt top layer. When the water is presented on the top layer of asphalt bitumen and sunlight will start to damage the asphalt surface by breaking the bond between the aggregate and asphalt bitumen. it will affect the asphalt surface losing its impermeable properties and will let water enter the surface. When water begins to enter into an asphalt surface it will lead to further cracks then the pavement failure occurs (Adlinge & Gupta, 2013).

2.3.7 Rutting

Rutting is channeled depressions in asphalt surface. When the deformation takes a place only in the asphalt concrete it may occur by plastic flow or consolidation. Asphalt cement stiffness is a big influence for rutting resistance of asphalt mixes while the Stiffer asphalt cement can increase rutting resistance (Xiao, Amirkhanian, & Juang, 2007).

2.4 Modification of Asphalt

The asphalt road's problems have a negative impact on the safe side for humans and to the economic side for the government especially for developing countries where financial resource for pavement maintenance is often insufficient and due to the limitations of bitumen regarding the temperatures, modification of bitumen is one of the best ways to improve the properties of bitumen various types of modifiers such as polymers, plastic, still slag, glass, were added to the base asphalt to improve the performance of the asphalt mixture (Cuadri, Partal, Navarro, García-Morales, & Gallegos, 2011a).

The usage of modified asphalt gives the ability to control the limits of mechanical stability of road surfacing by enhancing the properties of some types of surfacing during a hard extremely conditions of services (Sarsam & Lafta, 2014). By using modifiers with asphalt showed increasing in performance by raising the cohesion of the bitumen, and increase the viscosity and decrease the thermal capability of the binder (Al-Khateeb & Al-Akhras, 2011). Some studies conducted that by using a minimum of 10% of modified bitumen leads to longer enduring streets with better execution (Sabadra, 2017).

Many studies conducted to modified asphalt and it concluded that by adding modifiers to asphalt its heat and strength resistance to reach the double and that leads to improving the shearing resistance it also showed that the density of modified asphalt is more than density of the base asphalt and it gains by increasing the content of modifiers so the water saturation, respectively, reduces (Kishchynskyi, Nagaychuk, & Bezuglyi, 2016).

Sarsam and Lafta studied different type of modified asphalts to find out the physical properties of it and, obtained result showed that by adding the modifiers to the base asphalt, the penetration value of asphalt cement decreased, while the Softening point of asphalt cement gained and Ductility of asphalt cement decreased (Sarsam & Lafta, 2014).

2.4.1 Polymer materials applied for modified asphalt

The polymer is a chemical compound with molecules and bond together to create a long repeating chain. It can be used in a different field due to its unique properties (Sabadra, 2017). Polymers widely used as a modifiers for binder it can be classified as the following: plastomers, thermoplastic elastomers, and reactive polymer, it has the ability to enhance the thermal capability of asphalt binders, each one of them has its particular impact according to their properties: Thermoplastic elastomers increase the resistance of the binder to fatigue by improving the elastic properties, reactive polymers and plastomers increase the resistance to deformation and also increase the stiffness, (Brasileiro, Moreno-Navarro, Tauste-Martínez, Matos, & Rubio-Gámez, 2019).

Using polymer-modified binders in asphalt to improve performance is one strategy that is available to the design engineer or specifier to mitigate the damaging effect of increasing traffic stresses to ensure asphalt roads do indeed meet their planned design life. Polymers are also used for road maintenance surfacing techniques, namely surface dressing and micro-asphalt (Robinson, 2005).

The usage of polymer modified bitumen showed the ability to increase the resistance of the mixture against rutting and thermal cracking. Furthermore, the incompatibility between the bitumen and polymers leads to phase segregation among the blends which limit the strength of pavement (Ali et al., 2017).

By modifying the bitumen with polymer, the polymers differ the viscoelastic properties and the strength of the Asphalt, by providing the ductility, improve the Fracture strength, increase the elastic response and improve the cohesive property (Yildirim, 2007).

A study conducted by Becker et al. (2001) the results indecated that the polymer used as modifiers in paving field due to its capability to enhance the physical properties of the binders, the introduction of polymer improves the rutting resistance, high temperature sensitivity, fatigue, stripping and thermal cracking. Mostly its used when durability and high performance are necessary (Becker & Méndez, 2001).

Elastomeric polymers can often result in a decrease in stiffness, although some improvement in deformation resistance and cohesive strength can be obtained Polymers are usually used to: reduce rutting, i.e., permanent deformation, improve asphalt cohesive strength, and reduce risk of low-temperature thermal cracking by reducing the temperature susceptibility of the bitumen (Robinson, 2005).

The role of polymers is essentially to make bitumen more elastic, to reduce the risk of permanent deformation caused by viscous flow under applied loading. For unmodified bitumen the phase angle increases with increasing temperature, however, by introducing appropriate polymers the elastic recoverable component is reinforced and the phase angle is decreased (Airey, 2003).

In a study for Burger et al.(2001) A frequency sweeps test was used in their study. The results obtained showed that when the polymer is added to the binder it increases its performance at low frequencies and under a high temperature means a decrease in resistance to deformation Compared to unmodified bitumen, the polymer modified binders had a more elastic response under these conditions. While it can be noticed that the addition of polymer doesn’t affect the binder response to loading in terms of the relative distribution between elastic and viscous response (Burger, Van de Ven, Jenkins, & Muller, 2001).

Studies conducted to polymer modified bitumen showed that when the polymer is added to bitumen it increases the softening point and impart a high elasticity to bitumen. On the other hand, it showed that the mixture has a lower temperature sensitivity. It has higher strength at high temperatures and lower strength at low temperatures (Kishchynskyi et al., 2016).

The role of polymers is essential to make bitumen shear more elastic, to reduce the risk of permanent deformation caused by viscous flow under applied loading. For unmodified bitumen the phase angle increases with increasing temperature, however, by introducing appropriate polymers the elastic recoverable component is reinforced and the phase angle is reduced accordingly of the types of polymers in everyday use it is the elastomeric polymers (Robinson, 2005).

One of the main limits of polymer modifiers is that the polymers are thermodynamically unsuited with asphalt due to the large differences of density, molecular weight, solubility and polarity between the polymer and the asphalt. This may lead to delamination of the composite during thermal storage, which cannot be noticed easily and badly affects the material (Fang, Yu, Liu, & Li, 2013).

The high cost of the polymer modifiers is the reason that affects a wide use of it and to improve the bonding of polymer elements, between themselves and with bitumen, plasticizer was added in a polymer composition in some situation (Kishchynskyi et al., 2016).

2.4.2 Nanomaterials applied for modified asphalt

Nanomaterials are of morphological features on the nanoscale, and especially have special properties stemming from their nanoscale dimensions (Fang, Yu, Liu, & Li, 2013). Many studies in airport engineering and highway field have been done to explore the utilize of nanomaterials as a modifiers for asphalt, and they found that when nanoparticles are added to the binder, the viscosity and the cohesion of asphalt can be increased, which mean the mixture may have a good performance under high-temperature conditions (Ezzat et al., 2016).

Abdelrahman et al.(2014) made an experimental on the NC-asphalt nanocomposite. The indicated results showed that Nano clay modification of asphalt enhances the physical properties of asphalt. Raising Nano Clay concentration in the binders increase the temperature susceptibility of asphalt, as well as rising the complex modulus, while decreasing phase angle (Abdelrahman, Katti, Ghavibazoo, Upadhyay, & Katti, 2014).

A study done by comparative test Jahromi & Khodaii. (2009) their study based on a comparative rheological test on the base bitumen and nanoclay modified bitumen. The essential rheological test by dynamic shear rheometer (DSR) is done on base bitumen and modified. The results showed that the present of nanoclay can change the rheological properties of bitumen by decreasing the phase angle and increasing the stiffness, it showed the capability to improve ageing resistances(Jahromi & Khodaii, 2009).

Amirkhanian et al. (2010) investigated and estimated the rheological properties of the binders containing various percentages of carbon nano particles under high temperature. Their test resulted that the viscosity of binders increased as the rate of nano particles increased, also an increase in failure temperature was noted, but the percent increase depends on the binder grade, phase angles were consistently reduced, addition of the particles resulted in more resistance to deformation and higher elasticity, while elastic and viscous modulus values showed an increase with the addition of nano particles. (Amirkhanian, Xiao, & Amirkhanian, 2010).

A study conducted by You et al. (2011) on the effects of nano -clays on the rheological properties of asphalt by blending surfactant- modified nano-clay at two percent and four percent by weight of asphalt. It was found that the addition of nano-clay increases the viscosity of the base binder across varying temperatures. Also, the nanoclay-modified asphalt showed that the phase angle was decreased while the complex modulus was increased which mean the binder has a good performance under high temperature (You et al., 2011).

studies conducted to asphalt modified with nanomaterial, it found that the aging resistance, thermal storage and rheological properties of asphalt modified with nanomaterials are improved, which increase the service life of the asphalt pavement (Fang, Yu, Liu, & Li, 2013).

The previous studies have reported that the performance of bitumen modified with nanomaterials shows that the complex shear modulus of modified bitumen improved while the phase angle decreased, indicating that the permanent deformation (rutting) of modified bitumen could be minimized (Ali et al., 2017).

A study conducted by Ezzat et al. (2016) to evaluate the Asphalt Binders Modified with Nanoclay and Nanosilica, it concludes that the mixture resistance to permanent deformation could be improved using the proper amount of nanomodifier and the nanomodified asphalt binder can be stored to be used after few days it can be up to 10 days without big effect on its properties obtained by modification process in the bingeing.

The nanomaterials have been introduced as another way to improve the properties of bitumen and enhance the compatibility among the bitumen and polymers. Nanomaterials have been developing and incorporated rapidly in the field of asphalt mixture as it has unique properties. These properties include high surface work, a large fraction of surface atoms, structural features, quantum effects, and spatial confinement (Saltan et al., 2018).

It was predictable that modification of bitumen with nanomaterials would improve the properties of bitumen including an increase of stiffness of bitumen which leads to be less susceptible to the temperature and improve the strength of bitumen against moisture damage. Some nanomaterials have been used to modify polymer modified bitumen such as; nanoclay, nanofibers, carbon nanotubes and nanosilica (Ali et al., 2017).

It can be noticed, although nano-materials are promising, some type of nano-materials are expensive and demands further research to exploring and optimizing the enhancement in the binder properties before field testing and applications (Ezzat et al., 2016).

Due to the limitation of time and a high cost of the materials and experiments, also the leakage in equipment therefor some studies were conducted to predict the behavior of modified bitumen using adaptive neuro-fuzzy inference System (ANFIS) and artificial neural networks (ANN). Using the Artificial intelligence models to solve the different type of real-life procedures in engineering and environmental field shows its productivity and capabilities by dealing with a non-linear characteristic. AI applications can be used in the modeling of different real-life procedure in the field of engineering due to their predictive capacities and nonlinear characteristics (Asadi, Hassan, Nadiri, & Dylla, 2014).

It is understood that complex real-world problems may require intelligent systems that possess human-like expertise within a specific domain, adapt themselves to changing environments, and be able to explain how they make decisions or take actions (Bradshaw, 1997).

2.5 Artificial Neural Networks (ANN)

ANN is a system for processing data by mimicking the idea of the way biological neurons work in a human brain. Using ANN as a research methodology, the key idea is to develop a novel model that learns from past experiences and produces new results based upon them (Naderpour & Mirrashid, 2018).

Ozturk et al, (2016) analyzed the possible application of ANN for predicting the HMA volumetric properties of mixtures prepared by Marshall Mix design procedures. For modeling purposes, aggregate gradation, the bulk specific gravity of aggregates and binder content was used as input data. One of the main conclusions of their study is that the ANN model could be used as a quality control tool for roadway agencies, which would lead to significant savings in time, cost and labor compared to traditional design processes (Ozturk, Saglik, Demir, & Gungor, 2016).

J. Lui et al. (2018) have attempted to predict the dynamic modulus of virgin asphalt mixtures and asphalt mixtures containing recycled asphalt shingles with data from four different projects. The input parameters included were sieve test results on aggregates, air voids, effective binder content, the viscosity of the asphalt binder, loading frequency, and recycled asphalt board contents. The suggested ANN model was compared with the iowa model and gave significantly higher prediction veracity than the iowa model (Liu, Yan, Liu, & Zhao, 2018).

Elbadawy et al. (2018), made a comparison study between ANN models and regression models with Witczak NCHRP 1-37A, Witczak NCHRP 1-40D, and Hirsch E* predictive models for predicting dynamic modulus of hot mix asphalt. The database contained the test results of volumetric properties, aggregate gradations, binder viscosity, complex shear modulus and phase angle experimental results obtained from mixes from KSA and Idaho State. The ANN models using the same input parameters gave better performance for 3 predictive models than regression models (El-Badawy, Abd El-Hakim, & Awed, 2018).

In a study conducted by M. Firouzinia and Gh. Shafabakhsh. (2018), it was stated that the asphalt mixtures are highly temperature susceptible and sole enhancement of binder rheological properties are not sufficiently able to overcome this problem. Thus additives should be applied in asphalt mixtures. In their study, the impact of Nano-silica addition at five different contents was investigated on the thermal sensibility of hot mix asphalt using experimental procedures and the ANN models. It was found that modifying asphalt mixtures with Nano-silica improved the temperature sensitivity and the ANN models were generated with 5 input parameters of the percentage of the void, aged sample situation, bitumen type, bitumen situation and temperature with training algorithm as Radial Basis Function (RBF) Which show the capability to give an accuracy result (Firouzinia & Shafabakhsh, 2018).

Tapkın et al. (2009) presented a study to predict the strain accumulation in polypropylene (PP) modified marshal specimens. The data observed from repeated creep tests were modeled in ANN and demonstrated positive similarities with the experimental observation results. The significance of their study was that for a specific type of asphalt mixture and predefined testing conditions the cumulative strains at the end of repeated Load creep tests could be conducted without applying destructive tests (Tapkın et al., 2009).

Abedali (2018), conducted a comparison study between the performance of Multiple Linear Regression models (MLR) and ANN with base asphalt binder considering temperature, frequency, dynamic viscosity, shear stress and strain as inputs and G* as output. Ziari et al. (2018), performed a similar study with carbon nanotube (CNT) modified the asphalt binders to predicting the rutting performance using MLR and ANN and considered the CNT content, test temperature, and loading frequency as input variables. Both studies demonstrated that the ANN prediction performance outperformed the MLR models (Abedali, 2015).

Kök et al. (2010), investigated the shear modulus of base and styrene-butadiene-styrene (SBS) modified binders with ANN using the five different SBS contents, bitumen temperature, and the frequency as inputs and used Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Pola- Ribiere Conjugate Gradient (CGP) as the training algorithms. It had appeared that the LM algorithm was the most favorable topology for predicting G* (Kok et al., 2010).

Venudharan and Biligri (2017), employed an Artificial Neural Network to predict rutting performance of asphalt binder with different Crumb Rubber (CR) ranges. The input parameters were considered as five different CR gradations, base binder viscosity, frequency, and test temperature. The various combinations of neural network architectures with varying algorithms of training and transfer functions were trained, and backpropagation learning algorithm with SCG as the training algorithm in a feed forward, two hidden layers neural network with 7 and 3 neurons were found to be the optimum model (Venudharan & Biligiri, 2017).

Xiao Laboratory research performed by Tapkin (2010), predicted the fatigue of bituminous mixture and the fly ash was added as a filler and the results showed that ANN can be considered as a good tool which can be used in the prediction process. He compared the results by applying from a single, double and triple-layer networks and find out that one layer of the ANN is enough to predict the fatigue of the mixture with the introduction of fly ash (Tapkın, Çevik, & Uşar, 2010).

Mirzahosseini et al. (2013), investigated the applicability of using ANN modeling to predict the rutting performance of dense asphalt mixtures. They used 6 input parameters to the network: Bitumen, filler, percentage of coarse aggregate, Marshall Quotient, VMA, and air voids. They used statistical measures to find the efficiency of the predictive tool. The used ANN model was found to be an excellent tool for predicting the flow number (a measure of repeated load permanent deformation) of asphalt mixtures (Mirzahosseini, Najjar, Alavi, & Gandomi, 2013).

Xiao et al. (2011), Used a serial of ANN models to predict the viscosity rate of crumb rubber modified (CRM) binders. Their results indicated that ANN models were able to predict the viscosity of CRM binders, and also, the models are applicable to other types of rubber (Xiao, Putman, & Amirkhanian, 2011).

2.6 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS can be considered as a universal estimator which is used to preform highly nonlinear functions. ANFIS has many advantages than the other artificial intelligence (AI) techniques because it represents the amalgamation of fuzzy logic and neural network techniques so it takes advantage of the merits and eliminates their drawbacks (Cüneyt Aydin, Tortum, & Yavuz, 2006).

According to previous studies, Adaptive Neuro-Fuzzy Inference System is able to estimate any plant with high accuracy it can be used in different fields such as engineering, business, transportation, or economics and, medicine, etc., (Kar, Das, & Ghosh, 2014).

In a study conducted by Cüneyt Aydin, A., et al (2006), 2 ANFIS models were used: HSC data and NSC data to predict the elastic modulus of concrete. The ANFIS results were compared with codes and some data obtained from the literature and the study was concluded that ANFIS is a good tool for modeling and predicting the complex modulus of bitumen and it showed the ability to evaluate the elements affecting complex modulus of asphalt before it moves to the site which will help to save time consumed.

A study by F. Khademi et al used three artificial intelligence techniques: Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Linear Regression (MLR) to predict the 28 days compressive strength of concrete using 14 different input variables. The obtained result that ANN and ANFIS models efficient in predicting the 28 days compressive strength of concrete and are recommended due to its high efficiency especially when high accuracy is needed. (Khademi, Jamal, Deshpande, & Londhe, 2016).

In a study of Yilmaz, M et al (2011), ANFIS was used to model the complex of base and ethylene-vinyl-acetate (EVA) polymer modified bitumen. The data was obtained from a dynamic shear rheometer (DSR) test. In the modeling process the EVA content, bitumen temperature, and frequency were the inputs data and the complex modulus was the output data. The ANFIS result was closely related to the actual the results they conclude their study that ANFIS can be used for modeling the complex modulus of bitumen under varying temperature and frequency and it is important method to evaluate the factors affecting it and Adaptive Neuro-Fuzzy Inference System can be considered as good tools which help reduce the time consumed.

CHAPTER 3
MATERIALS AND METHODOLOGY

3.1 Experimental Procedures

3.1.1 Materials and properties

The base bitumen utilized was of 80/100 penetration grade. ASA in the form of white powder was used as the polymer modifier at 5% concentration to the weight of base bitumen. Two different nanomaterials, namely nano copper and nano calcium, were obtained from a company in China and mixed with ASA at 3% and 5% compositions to form two different binders modified with polymer composites. Samples were prepared using a high shear mixer at a constant temperature of 170 ^{o}C and at a speed of 5000 rpm for 90 minutes in order to make homogeneous mixtures. Evaluation of the physical properties of the unmodified, polymer modified and polymer nanocomposite modified binders were conducted by penetration (ASTM D5) and softening point (ASTM D36) tests. Physical properties of the binders were also used as input parameters in computational modelling. Findings are presented in Table 3.1.

Table 3.1: Physical properties of samples

Material	Penetration (dmm)	Softening point (^{o}C)
Bitumen 80/100	82	46
5% ASA	74	50
3% ASA-Nano copper	66.4	56
5% ASA-Nano copper	69.1	55
3% ASA-Nano calcium	75.3	55
5% ASA-Nano calcium	76.9	53

3.1.2 Dynamic shear rheometer

A Dynamic Shear Rheometer (DSR) was used to observe the rheological properties of modified binder samples mentioned in the Materials and Properties section above. Tests were performed at temperatures ranging from 46 ^{o}C to 82 ^{o}C with increments of 6 ^{o}C as specified in Superpave PG guidelines. Temperature control of the samples was achieved by a fluid bath system and temperature control unit in order to keep temperatures constant and uniform over the range of temperatures in which the experiments were conducted. The DSR equipment shown in Figure 3.1 consists of top and bottom plates. Samples of 1-mm thickness were sandwiched between 25-mm diameter plates, where the bottom plate was fixed and the top plate was oscillating back and forth with ranging frequencies to simulate shearing action. The tests were performed at nine different frequencies ranging from 0.159 Hz to 15.92 Hz. The tests were software controlled, while measured stresses and resulting strains were obtained in terms of complex modulus (G*) and phase angle (δ), which are considered as the most significant parameters to define the rutting (G*/sin δ) and fatigue (G*.sin δ) performance of asphalt binders. The effect of temperature on the performance of asphalt binders was illustrated using isochronal plots, master curves, and rutting performance graphs. G* results were used in the construction of master curves. In order to represent the results in a single curve known as a master curve, a reference temperature of 64^{o}C was defined and frequencies were shifted relative to this temperature. Numerous shifting methods have been used in the literature, namely the Williams–Landel–Ferry (WLF) equation, the Laboratoire Central des Ponts et Chaussées (LCPC) approach, the modified Kaelble equation, the viscosity–temperature-susceptibility (VTS) equation, the Arrhenius equation, and the log-linear approach, (Ali, S.I.A., et al., 2015). The log-linear approach was adopted in this study using relevant shift factor constants at each test temperature to obtain the best fitting master curve.

Figure 3.1: Schematic presentation of DSR (Dynamic Shear Rheometer)

3.2 Modeling Procedures

In this study, FFMLP and ANFIS approaches are applied to calculate the complex modulus for base asphalt and nanocomposite modified asphalt. The inputs of those models are softening point, penetration, Temperature, and frequency. The data were observed from a dynamic shear rheometer (DSR) test. The resulted G* from the artificial intelligent techniques compared with the experimental result then the resulted complex modulus from Artificial neural networks model and from Adaptive neuro-fuzzy inference system model are compared with together. Conclusions can be made upon the comparison. The general procedure of how this study was conducted is illustrated in Figure 3.2.

A set of 381 data points from six different blends of AC at different concentrations were used in the modelling of ANN and ANFIS, the data is provided in Appendix 1. Furthermore, 267 (70%) of the data points were used for training the network, 57 (15%) of the data points were used for checking and 57 (15%) of the data points were used for testing of the models. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set, therefore a validation data set is used to check and control the potential for the model overfitting the data. The testing data set has significance since it shows the prediction capacity of the network for the untrained data set.

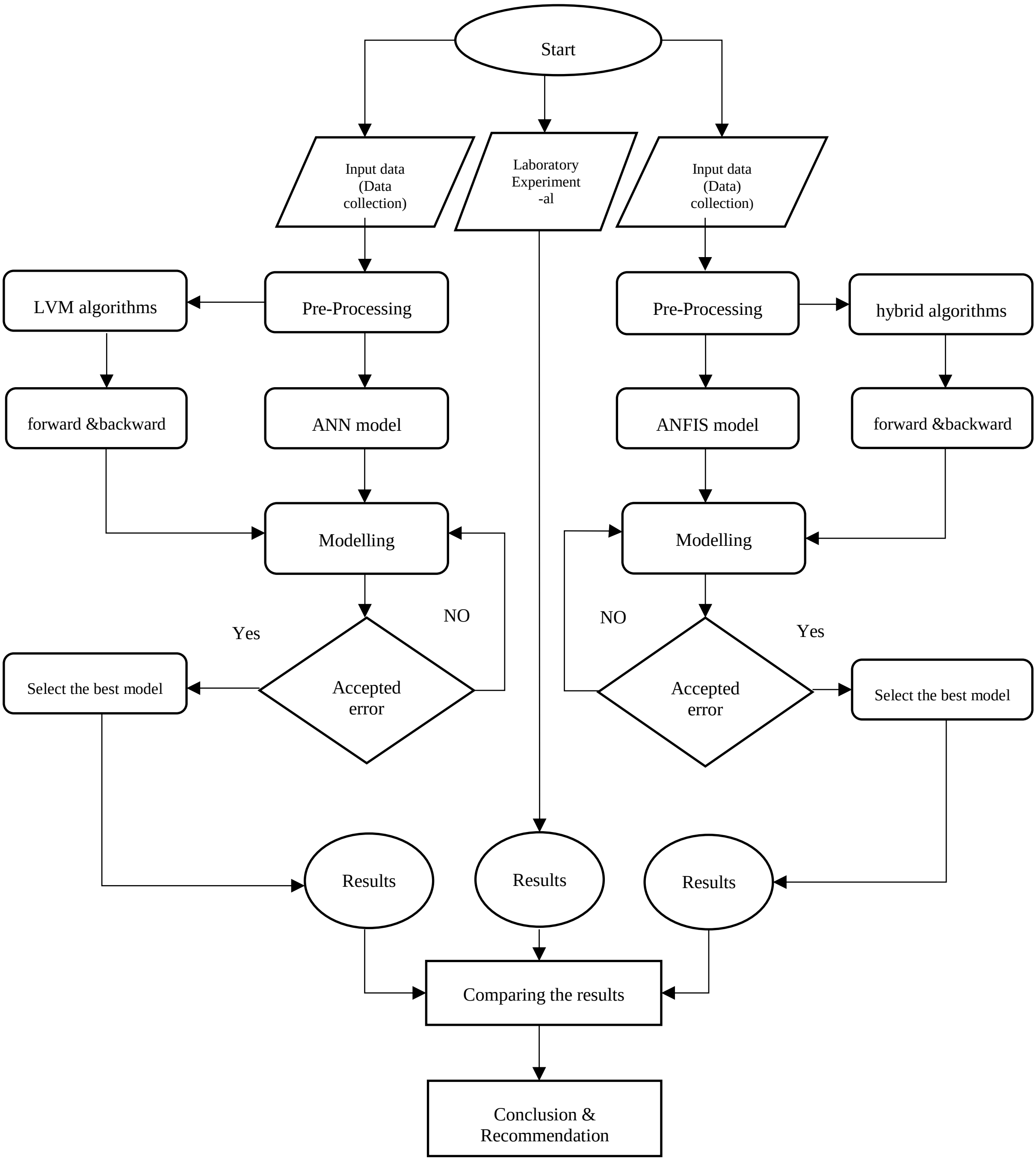

Figure 3.2: Flowchart of the study

3.3 Artificial Neural Network

Artificial neural networks (ANN) belong to the learning machine family, which uses a computational approach to develop predictive models for desired parameters by simulating the way biological neurons work in the human brain, (Liu, J., et al., 2018). Numerous types of ANN have been adopted in the literature. A feedforward multilayer perceptron (FFMLP) was adopted in this study. With this type of ANN, the learning is supervised, which indicates that for a given set of input vectors, the output vectors are provided to the network and the system is expected to adjust its weights using forward and backward calculations to minimize the prediction errors, which is also known as the learning phase.

The structure of MLP is divided into three layers, which are strongly interconnected with artificial neurons. The initial layer is the input layer x_i where the input signals are stored for a given set of input parameters x_{ai}. Input parameters in this study were the physical properties of the blends (penetration value and softening point) and mechanical test parameters (temperature and frequency).

$$x_i = (x_{1i}, x_{2i}, \dots \dots \dots x_{ai}) \qquad i = 1, \dots \dots, n \tag{3.1}$$

The final layer is the output layer y_i, where the targeted parameter, G*, was expected to be predicted in this study.

$$y_i = (y_{1i}, y_{2i}, \dots \dots \dots y_{bi}) \qquad i = 1, \dots \dots, n \tag{3.2}$$

The intermediate layer is called the hidden layer and it is devoted to the calculations that formally connect the input layer x_i with the output layer y_i.

A weighted sum of the values of the input variables is computed through the weights that are associated with each connection by eqn. 3.3;

$$y = \sum_{i=1}^{a} w_i x_i + w_0 \tag{3.3}$$

Where w_i is the weight associated with the i^{th} input parameter, x_i is the data corresponding to the input parameter and w_o is the bias.

The output value is calculated in a forward pass using a transfer function. Numerous transfer functions such as the Heaviside step function, sigmoidal, or hyperbolic tangent have previously been used in the literature. Utilization of the activation function is highly dependent on the nature of the dataset and the type of model desired to be developed. In this study, a hyperbolic tangent as expressed in eqn. 3.4 was adopted.

$$f(a) = \frac{e^{a}-e^{-a}}{e^{a}+e^{-a}} = \frac{2}{1+e^{-2a}} - 1 \qquad (3.4)$$

The above-mentioned procedure is an iterative process. The network performs a series of forward and backward calculations to adjust its weights in order to achieve the most accurate predictions to the target values, which is also called the training of the neural network (Baldo, Manthos, & Pasetto, 2018).). In this study, MATLAB (Mathwork Inc R2013a) was used in order to develop ANN models. Although various training algorithms are available in MATLAB, the selection of the training algorithm depends on the type of neural network to be modelled and the structure and complexity of the data to be fed to the network. The Levenberg-Marquardt (LVM) training algorithm was observed to be the most suited algorithm considering the structure of the dataset observed from the DSR oscillation tests. The configuration of the applied neural network is shown in Figure 3.3.

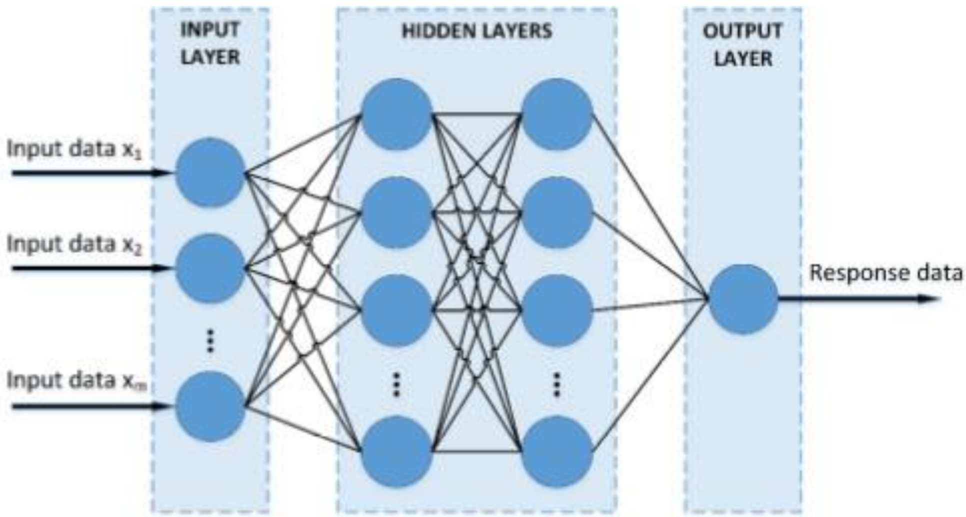

Figure 3.3: Configuration of the selected artificial neural network

3.4 Adaptive Neuro-Fuzzy Inference System

Fuzzy modelling is a branch of system identification which deals with the construction of a fuzzy inference system or fuzzy model that can predict and explain the behaviour of an unknown system described by a set of sample data (Jang et al., 1998). Adaptive neuro-fuzzy inference system (ANFIS) is an efficient approximator model that combines neuro-fuzzy systems and the other machine learning techniques. The ANFIS's map is significantly different from that of the ANN. It goes from input characteristics to input membership functions, from rules to a set of output characteristics, then to output membership functions, to a single-valued output, or to a decision associated with the output.

There are two methods in ANFIS modeling to be used first one Mamdani fuzzy inference and second one Sugeno fuzzy inference, those methods are similar to each other in the first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, while the main difference between Sugeno and Mamdani is that the Sugeno output membership functions are either linear or constant. The Sugeno method was used in this study because it is a more compact and computationally efficient than a Mamdani method. The Sugeno system is suited for modeling nonlinear systems by interpolating between multiple linear models and it uses adaptive techniques for constructing fuzzy models which can be used to customize the membership functions so that the fuzzy system best models the data (User's).

ANFIS is a class of adaptive, multi-layer feedforward networks, which is comprised of input and output variables and fuzzy rule base of Tabkagi-Sugeno fuzzy if-then rules for a first-order Sugeno fuzzy model, (Tavakkolizadeh, M. and H. Saadatmanesh, 2003). A two rule-based ANFIS model with x and y inputs and f output is expressed in eqns.3.5 and 3.6.

Rule (1): If x is A_1 and y is $B_{1,}$ then $f_1 = p_1x + q_1y + r_1$ (3.5)

Rule (2): If x is A_2 then y is B_2 then $f_2 = p_2x + q_2y + r_2$ (3.6)

Where A_1 and A_2 are the input membership function (MFs) for the input layer, B_1 and B_2 are the inputs (MFs) of y, respectively. The output function parameters are p_1, q_1, r_1 and p_2, q_2,r_2. The framework of ANFIS consists of five layers, which are described below:

Layer 1: This layer is responsible for the production of the input variable membership grades in each node. The values of membership functions for each $i\ th$ nodes are defined in this layer:

$$Qi^1 = \mu Ai\ (x) = \frac{1}{1+\left[\left(\frac{x-Ci}{ai}\right)^2\right]^{bi}} \quad (3.7)$$

Where x is the input to node i and Ai if the linguistic label associated with this node function, ai,bi,ci is the parameter set that changes the shapes of the membership function.

Layer 2: In this layer, each node multiplies by the incoming signals, as shown by eqn. 3.8:

$$Qi^2 = wi = \mu Ai\ (x)\ \mu Ai\ (x) \times \mu Bi\ (y), I = 1, 2\ \ldots. \quad (3.8)$$

Layer 3: This layer is responsible for the normalized firing strength for the membership values in node $i\ th$ by the equation:

$$Qi^3 = wi = \frac{w1}{(w1+w2)}\ \ i = 1, 2\ldots. \quad (3.9)$$

Layer 4: In this layer, the relationship between the input and output value can be established by the equation:

$$Qi^4 = wi\ (pi\ x + qi\ y + ri) \quad (3.10)$$

Where wi is the output from layer 3, and pi, qi, ri are the parameters. Parameters in this layer will be referred to as ‘consequent parameters.

Layer 5: This layer includes only one node and it makes a summation of all the output results which comes from the previous node and gives the output in a single node by the equation:

$$Qi^5 = \frac{\sum iwi\ fi}{\sum iwi} \quad (3.11)$$

The learning rule of ANFIS is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks (Rumelhart, Hinton, & Williams, 1985). The optimization parameters are i ,bi ,ci which are the premise parameters, while pi ,qi ,ri are the consequent parameters. A hybrid-learning rule was employed in this research, which involves gathering the gradient descent and the least-squares method in order to find the appropriate set of preceding and consequent parameters (Aqil, Kita, Yano, & Nishiyama, 2007). The advantage of using a hybrid-learning rule was that it also seemed to be significantly faster than the classical back-propagation method (Jang et al., 1998). Fig 3.4 shows the structure of ANFIS.

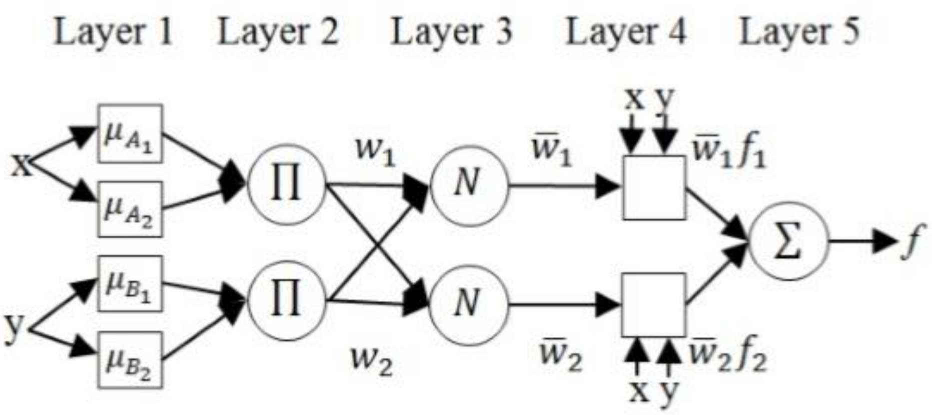

Figure 3.4: structure of ANFIS (Talpur, Salleh, & Hussain, 2017)

The hybrid-learning procedure includes two passes, namely the forward pass and the backward pass. In the forward pass, the functional signals will go forward till layer 4 and the least-squares technique will identify the consequent parameters. In the backward pass, the error rates transmit backward and the gradient descent will update the premise parameters. While the values of the premise parameters are fixed, it’s possible to express the overall output as a linear combination of the consequent parameters (Cüneyt Aydin et al., 2006). Figure 3.5. show the Hybrid-learning procedure of ANFIS.

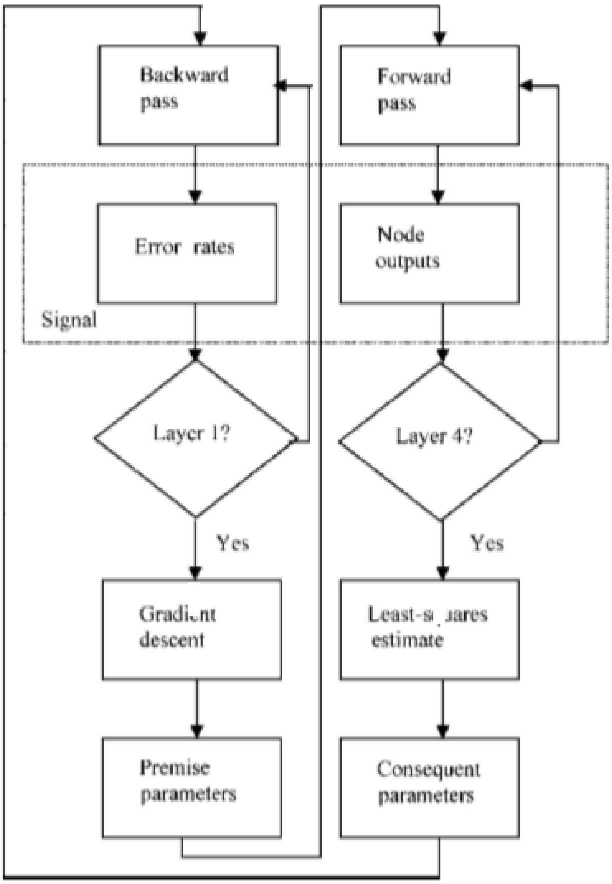

Figure 3.5: Hybrid-learning procedure of ANFIS (Cüneyt Aydin et al., 2006).

3.5 Data Normalization and Performance Evaluation

To ensure equal attention is given to all inputs and output, and to eliminate their dimensions, the data used in this study were scaled between 0 and 1. The main advantage of data normalization before the application of Al models is to reduce data redundancy, to avoid numerical difficulties in the calculation, and to avoid the using of attributes in bigger numeric ranges that overshadow those in smaller numeric ranges (Sola & Sevilla, 1997). Therefore, the data used in this study were normalized using Eqn. 3.12 prior to ANN and ANFIS modelling.

$$\frac{x-x_{min}}{x_{max}-x_{min}} \qquad (3.12)$$

ANN models and ANFIS models developed with training and testing data sets were evaluated for their prediction capacity using the performance indicator metrics. Coefficient of determination (R^2), covariance (COV), mean squared error (MSE) and root mean squared error (RMSE) were the common statistical performance indicators adopted in various studies (El-Badawy et al., 2018; Kok et al., 2010; Liu et al., 2018).). R^2 and RMSE as expressed in Eqn. 3.13 and 3.14 were adopted in this study.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\gamma}_i - \gamma_i)}^2 \qquad (3.13)$$

$$R^2 = 1 - \left[\frac{(\gamma-\hat{\gamma})^2}{(\gamma-\gamma_{mean})^2}\right] \qquad (3.14)$$

Where γ_i is the data observed in the experiments, $\hat{\gamma}_i$ is the ANN model predicted data and n is the number of target values.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Dynamic Mechanical Analysis Test

DSR oscillation tests were conducted on base bitumen, polymer modified bitumen (5% ASA) and polymer composite binders of (ASA-Nano copper and ASA-Nano calcium) at 3% and 5% concentrations in order to understand the effect of test parameters and the influence of modification on the performance of the modified binders. The performance of the modified binders was observed in a range of temperatures (46^{o}C-82^{o}C) and frequencies (0.159 Hz-15.92 Hz), while isochronal plots, master curves, and rutting parameter plots were used in the evaluation of performance characteristics.

4.1.1 Isochronal plots

Isochronal plots were used to represent complex modulus over a range of temperatures at constant frequencies. Isochronal plots assisted in making a comparison for G* at given temperatures. Furthermore, temperature susceptibility of asphalt cement can be interpreted using isochronal plots. On this basis, complex modulus versus a range of temperatures is plotted in Figs. 4.1 and 4.2 at two constant frequencies of 0.159 Hz and 15.92 Hz, respectively. It can be observed that all modified blends demonstrated significant enhancement in G* and reduced temperature susceptibility compared to base AC. 3% ASA-Calcium blends showed the greatest enhancement, while the 5% ASA blends showed the least. It was also noted that enhancement in the properties of the modified blends was greater at higher frequencies and lesser at lower frequencies, which is in compliance with numerous studies conducted on styrene-butadiene-styrene (SBS), natural rubber latex (NR) and epoxidized natural rubber (ENR).

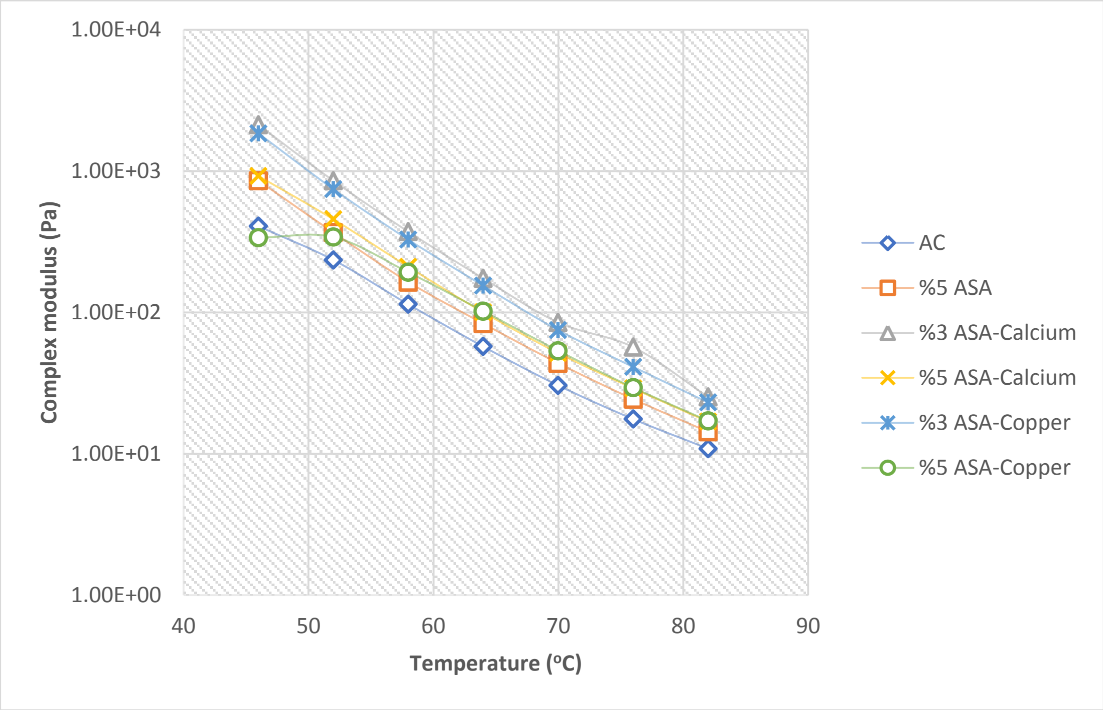

Figure 4.1: Isochronal plot of G* at 0.159 Hz

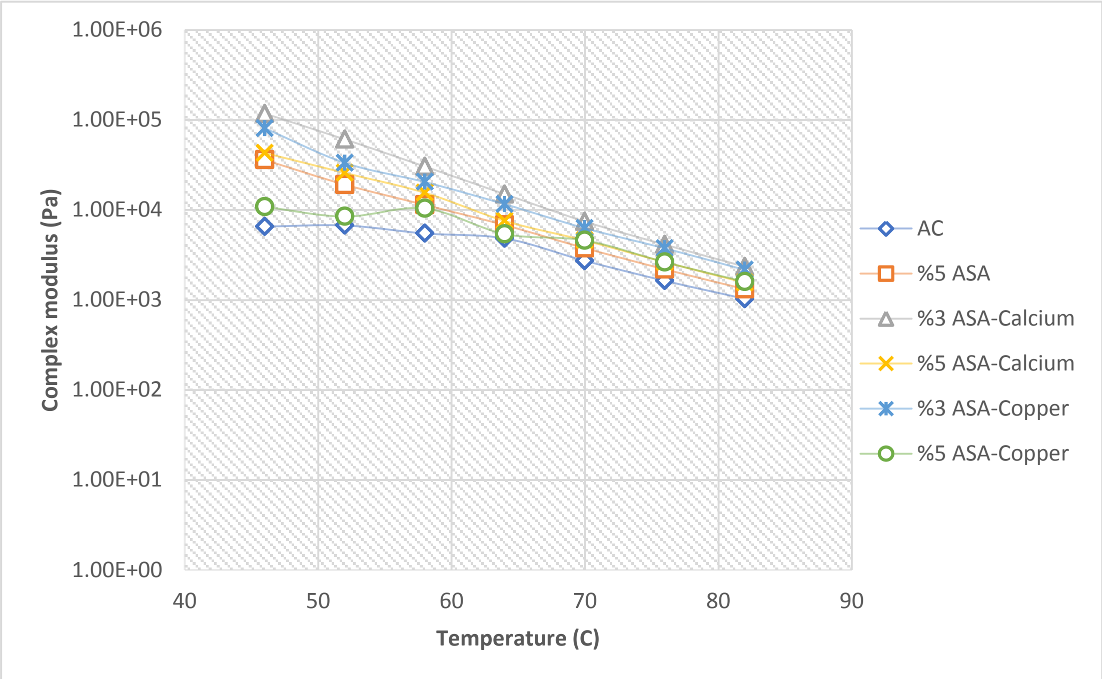

Figure 4.2: Isochronal plot of G* at 15.92 Hz

4.1.2 Rheological master curves

Master curves allow the representation of rheological measurements such as G* and δ to be plotted on a single curve at a range of temperatures and frequencies. In order to construct the master curves, a reference temperature of 64 ^{o}C was selected and all other temperatures were shifted horizontally with respect to time to obtain a smooth curve. Shifting was performed using constant numerical shift factors at each elevated temperature between 46^{o}C-82^{o}C. Fig. 4.3 presents the complex modulus master curve for different blends.

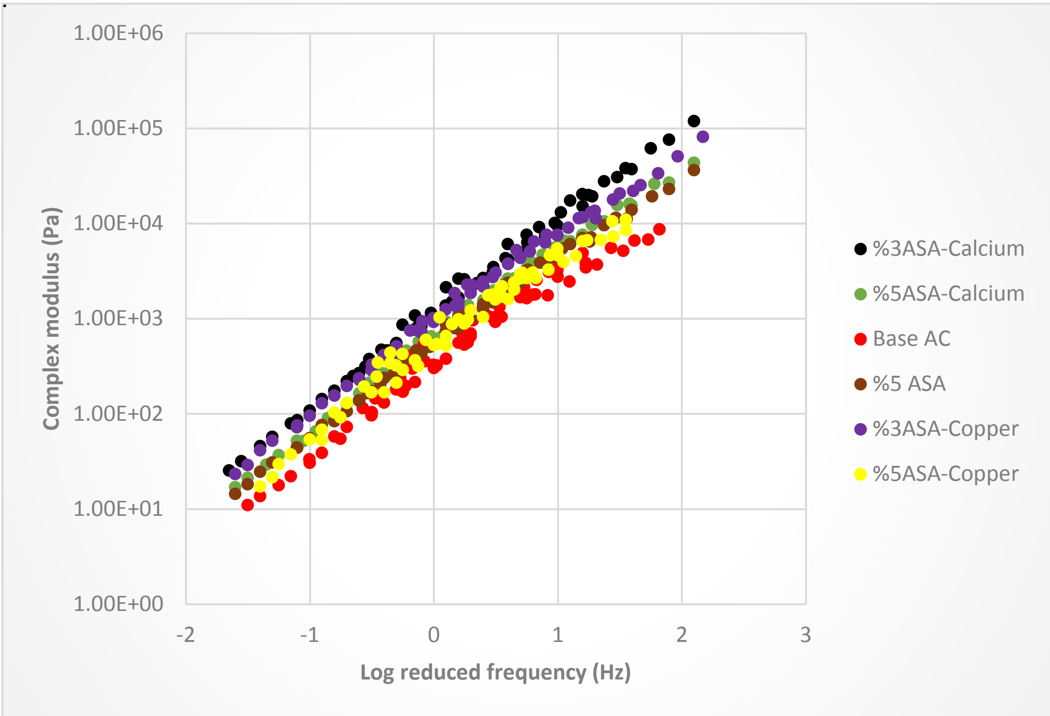

Figure 4.3: Complex modulus master curves at 64 ^{o}C reference temperature

It can be observed that consistent improvements in the complex modulus with polymer and polymer composite modified samples were achieved. An increase in the complex modulus slightly larger than 1kPa was noted between base AC and ASA-Calcium at 3% concentration. It can further be observed that up to 3% concentrations, both polymer composite blends showed significant improvement in rheological properties; however, at 5% concentrations, reduction in the enhancement of complex modulus was observed. The cause for the different behavior could be linked to inhomogeneity of blends and the potential of particles to form clusters at higher concentrations of modification. Blends of 5% ASA-Copper and 5% ASA-Calcium are therefore not considered preferable blends to modify asphalt cement as the enhancement in complex modulus was insignificant compared to 5% polymer (ASA) modified AC. It is also noteworthy to mention that in a study conducted by Ali et al., (2015), complex modulus of 10^8 Pa was achieved with 5% ASA modified asphalt cement with a bitumen penetration grade of 60/70. In this study, bitumen grade 80-100 was used in the blends and complex modulus results yielded were slightly above 10^5 Pa, indicating that together with the type and concentration of modifier used, the penetration value of base bitumen had a significant influence on the rheological behaviour of modified asphalt cement.

4.1.3 Rutting parameter

The failure of bitumen at high temperatures was related to the rutting resistance performance of AC. Rutting parameter known as $G^*/\sin\delta$ can be evaluated from DSR oscillatory test results. In order to resist rutting, AC is preferred to be stiff and elastic. As can be deduced from the formula, higher G* (stiffness) and lower δ (elasticity) would lead to higher rutting resistance. On this basis, as specified in the ASTM standards, the rutting parameter should not be less than 1kPa for unaged samples. The effects of rutting on base and modified binders are shown in fig. 4.4. It can be observed that all blends including base AC have passed the ASTM specification of a minimum rutting parameter of 1kPa at 82 ^{o}C. It is also noted that polymer nanocomposite blends have performed better in terms of temperature susceptibility compared to base AC and 5% ASA modified binders. Polymer composite blends for ASA- Nano calcium and ASA- Nano copper at 3% has been shown to have higher rutting $G^*/\sin\delta$ than at 5%. This might be explained by the occurrence of agglomeration due to poor dispersion of particles in the asphalt matrix during the mixing progress.

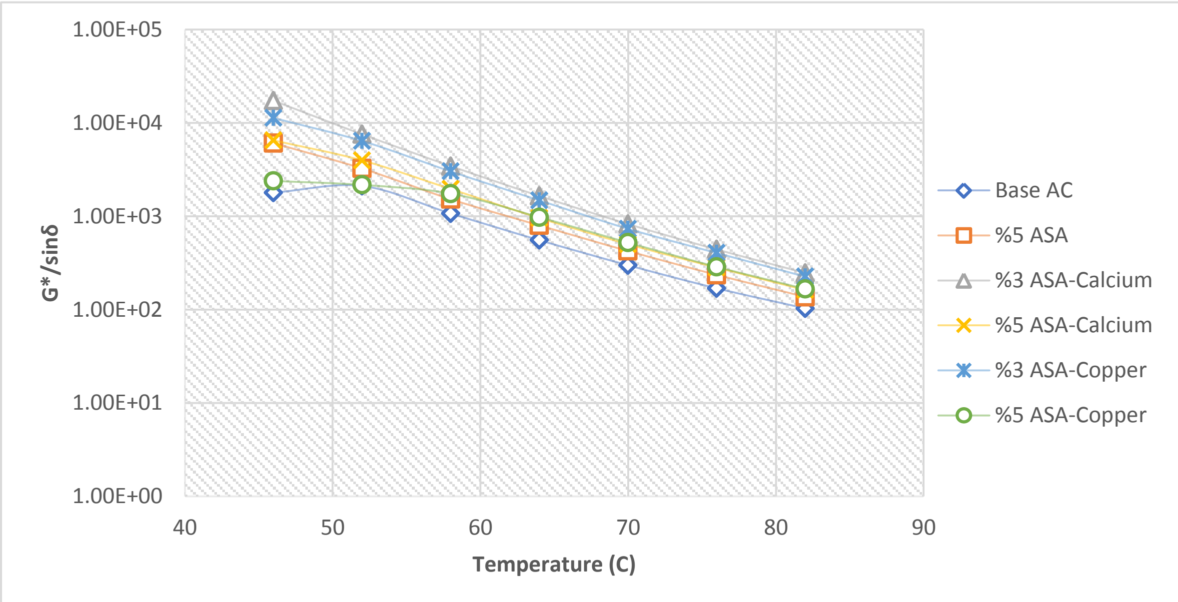

Figure 4.4: Effect of temperature on the rutting parameter

4.2 Artificial Neural Network Model

ANN Model development was performed in a numerical computing environment using MATLAB (MathWork Inc R2013a). A Feed-Forward Multilayer Perceptron model with three layers, namely the input, hidden and output layers, was adopted. Physical properties (penetration and softening point) and mechanical test parameters (temperature and frequency) were the input variables and G* was the targeted output parameter. A total of 381 data points obtained from the experimental investigations were used in the ANN modelling. 70% of the dataset was used for training and 15% for checking the network and 15% for testing of the network.

Various network structures and training algorithms were utilized with the purpose of obtaining the best neural network model. The backpropagation learning method with Levenberg-Marquardt training algorithm, 4-5-1 network topology and hyperbolic tangent as the activation function were found to be the optimum model at predicting close estimates of G*. The training performance of the ANN is given in fig. 4.5, where the variation of mean squared error with training epochs is illustrated.

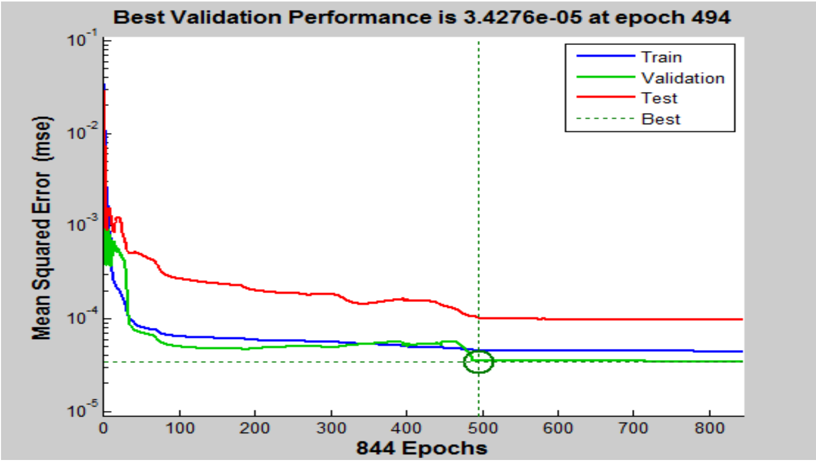

Figure 4.5: Neural network training performance

The regression performance of the neural network model was evaluated by the statistical goodness of fit measure R. Herein, values close to 1 indicated that the targeted outputs were predicted with high accuracy, whereas values below 0.9 were considered to indicate the incapability of the neural network to learn the pattern in the dataset. Fig. 4.6 presents the measure of goodness of fit for the model using the testing dataset.

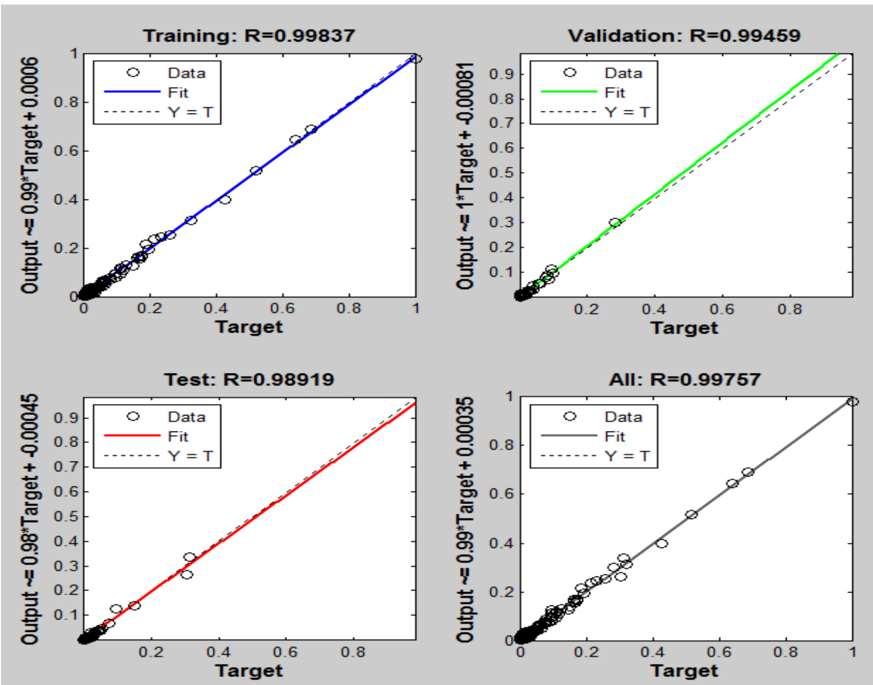

Figure 4.6: Experimental versus predicted G*

In terms of performance indicator metrics, coefficient of determination R^2 values of 0.9951 and 0.9960 and RMSE values of 0.00937 and 0.008295 were computed for training and testing datasets, respectively. The significance of observing high R^2 values with training and testing data sets is that the model showed a distinct level of generalizability with both the trained and untrained dataset. Fig. 4.7 further demonstrates a point to point comparison between the experimental and ANN predicted data points.

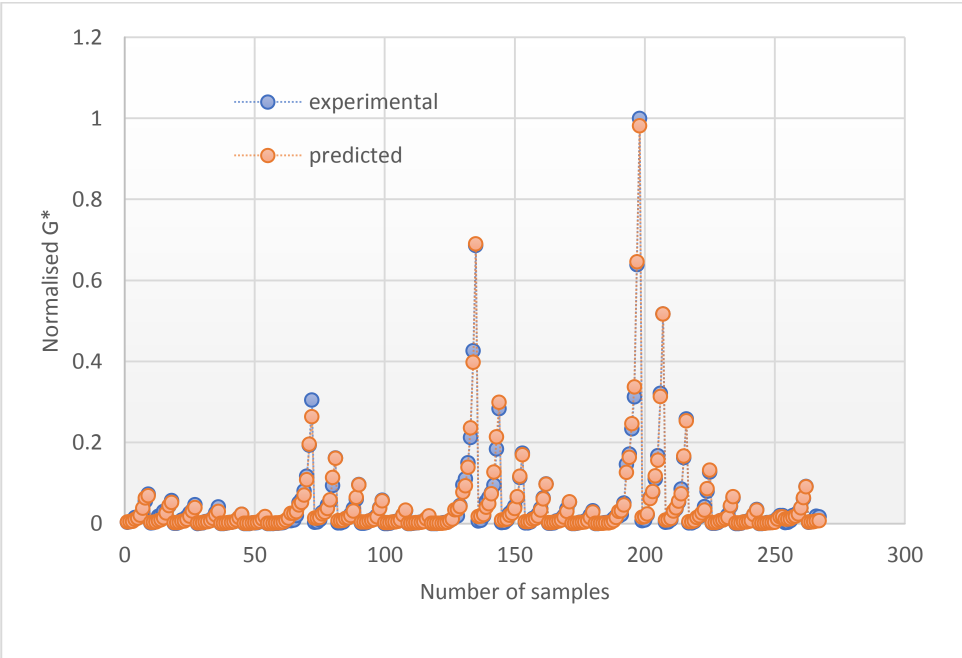

Figure 4.7: Point to point comparison between experimental and ANN predictions for G*

4.3 Adaptive Neuro-Fuzzy Inference System Model

ANFIS Model development was performed by using a Sugeno type fuzzy inference algorithm, while the membership function parameter was defined by a set of the given input-output data via a hybrid optimization algorithm. In order to have the best ANFIS construction, a trial and error procedure was adopted for the formulation of the structure of the ANFIS model. Mechanical test parameters (temperature and frequency), and physical properties (penetration and softening point) were the input variables and complex modulus G* was the targeted output parameter. A total of 381 data points obtained from the DSR experimental investigations were used in the ANFIS modelling. As mentioned in the previous chapter the classified dataset used for training, validation (checking) and, testing the network. In this way, the data redundancy was reduced. Additionally, in ANFIS. The performance of the ANFIS model with the testing dataset is represented in Fig. 4.8.

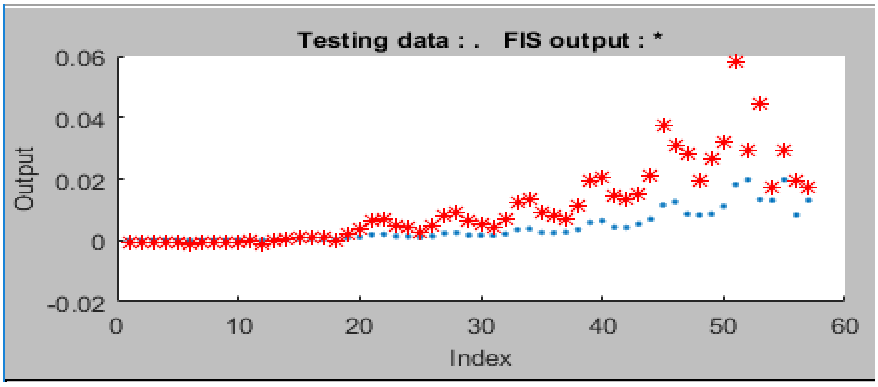

Figure 4.8: ANFIS network Checking performance

The statistical goodness of fit measure R was used to evaluate the regression performance of the ANFIS model. The target output was considered to be predicted with high accuracy if it was close to 1, while if it was below 0.9, it was considered as an indication that the ANFIS model was not able to test the data set. The coefficient of determination R^2 values of 0.998, 0.754 and 0.92 and RMSE values of 0.00488, 0.007786 and 0.011523, were computed for the training, checking and testing datasets respectively. Fig.4.9 presents the measure of goodness of fit for the model using all the datasets.

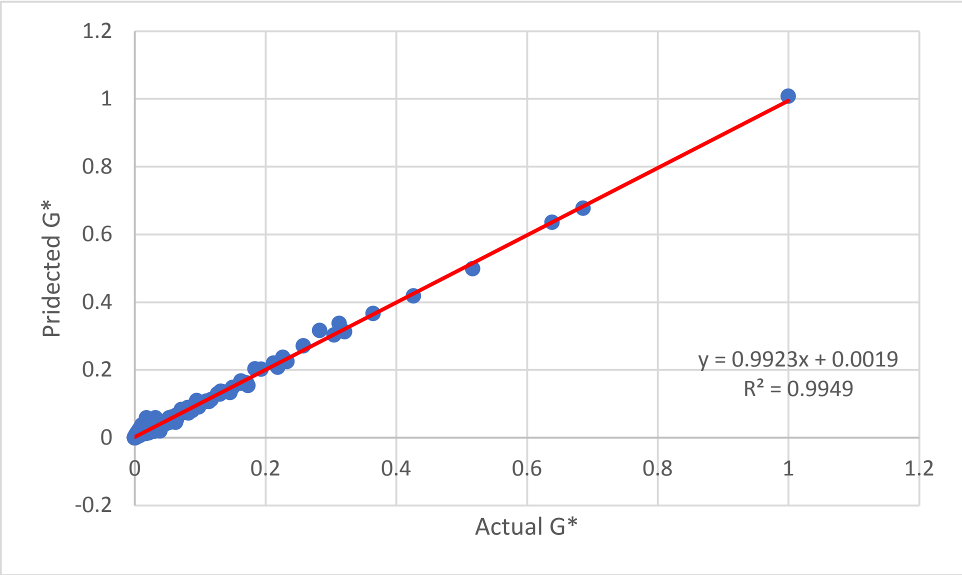

Figure 4.9: Measure of the goodness of fit for ANFIS predictions for G*

Fig. 4.10 further demonstrates a point to point comparison between the experimental and ANFIS predicted data points.

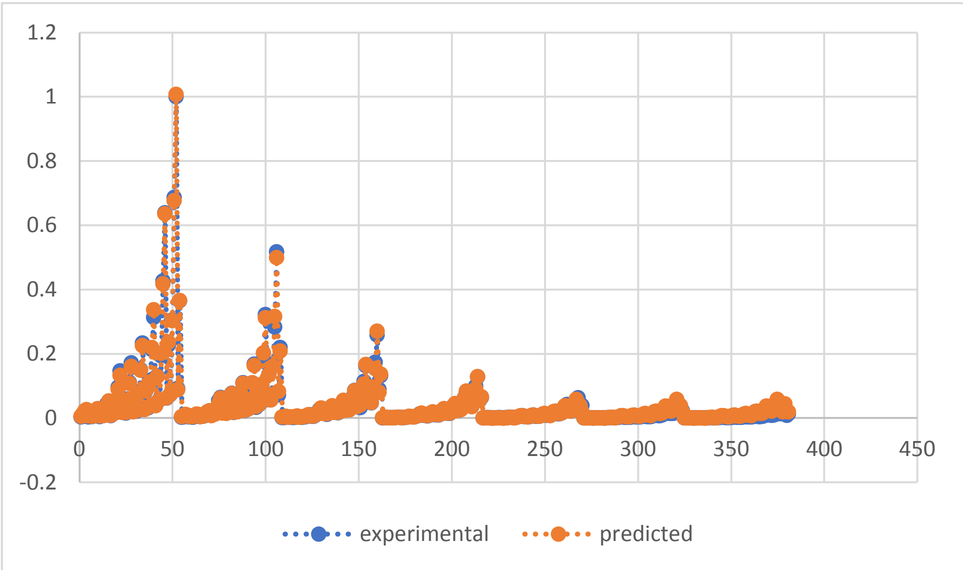

Figure 4.10: Point to point comparison between experimental and ANFIS predictions for G*

4.4 Comparison between ANN and ANFIS

The obtained results from both models indicated that Maximum G* was reached with 3% ASA-Nano calcium modified binder. While the complex modulus tends to be greater at low temperatures and start to decrease when the temperature starts to increase, as the experimental result showed. The values of R^2 and RSME for training, validation, and testing for both ANN and ANFIS models are shown in Table 2. According to the results showed in table 2, it can be noticed that both the ANN and ANFIS models are capable enough in predicting the viscoelastic properties of the binder. The higher accuracy of ANN and ANFIS models could be due to the nonlinear relationship between the parameters which can be presented better by those applications. As it is illustrated in Table 2, the ANN model has a higher value of R^2 as compared to ANFIS. Therefore, the ANN model is found to be the most efficient model in predicting the physical properties of asphalt.

Table 4.1: The values of R^2 and RSME for both ANN and ANFIS models

	Training		Validation		Testing	
Model	DC	RMSE	DC	RMSE	DC	RMSE
ANN	0.9951	0.00937	0.99459	0.00736	0.9960	0.008295
ANFIS	0.998	0.00488	0.754	0.007786	0.92	0.011523

CHAPTER 5
CONCLUSIONS AND RECOMMENDATION

5.1 Conclusion

The physical properties, stiffness (G*) and rutting resistance of unmodified, polymer modified and polymer Nano composite materials of Nanocopper and Nanocalcium modified at 3% and 5% concentrations to the weight of bitumen were investigated under a range of temperatures and frequencies using DSR. Furthermore, analytical techniques were employed to conceptualize and develop ANN and ANFIS based models to predict the rheological properties of binders in terms of G* in order to overcome the time and resource-related drawbacks of experimental procedures. According to the test results and analytical models' performance evaluation, the following conclusions can be drawn:

- Maximum enhancement in G* was observed to be slightly above 1.00 E+05 Pa with 3% ASA-Nano calcium modified binder.
- Increasing the polymer nanocomposite material content enhanced the properties of the asphalt binder up to 3% concentration. However further use of modifier at 5% concentration to the weight of bitumen resulted in lower G* and rutting resistance, which is considered to be due to incompatibility of bitumen with the modifier.
- It was observed that 5% ASA modified and 5% ASA-nanocalcium and 5% ASA-nanocopper modified blends demonstrated almost equal enhancement in the rheological properties of asphalt binder.
- The ANN multilayer perceptron model developed with Levenberg-Marquardt training algorithm, hyperbolic tangent as the activation function in a 4-5-1 neural network structure was able to predict experimental observations with R^2 and RMSE values of 0.9960 and 0.008295, respectively.
- The ANFIS Model developed and the proportions of training, validation and testing were selected, by using a Sugeno type fuzzy inferencece algorithm, while the membership function parameter was defined by a set of the given input-output data via a hybrid optimization algorithm, The ANFIS model was able to predict experimental observations with R^2 and RMSE values of 0.9949 and 0.006755, respectively.

5.2 Recommendation

The DSR tests were performed using 80/100 penetration grade bitumen in the base and modified binders. According to a study conducted by Ali et al., (2015) the ASA modified bitumen with base 60/80 grade provided higher G* values and therefore, it is significant that among the types of modifier materials, the penetration grade of base bitumen significantly influences the performance of asphalt binders. Furthermore, although the ANN and ANFIS models developed herein provided accurate predictions of the experimental outcomes, the performance of the models could be enhanced with a larger dataset. The performance characteristics of asphalt binders can also be modelled using an Extreme learning machine (ELM), Support vector machines (SVM) and genetic algorithms. On this basis, it is recommended that future studies should focus on these models with larger datasets and the results could be compared to those reported by the present study.

REFERENCES

Abdelrahman, M., Katti, D. R., Ghavibazoo, A., Upadhyay, H. B., & Katti, K. S. (2014). Engineering physical properties of asphalt binders through nanoclay–asphalt interactions. *Journal of Materials in Civil Engineering*, *26*(12), 04014099.

Abedali, A. H. (2015). Predicting complex shear modulus using artificial neural networks. *Journal of Civil Engineering and Construction Technology*, *6*(3), 15-26.

Adlinge, S. S., & Gupta, A. (2013). Pavement deterioration and its causes. *International Journal of Innovative Research and Development*, *2*(4), 437-450.

Airey, G. D. (2003). Rheological properties of styrene butadiene styrene polymer modified road bitumens☆. *Fuel*, *82*(14), 1709-1719.

Al-Khateeb, G. G., & Al-Akhras, N. M. (2011). Properties of Portland cement-modified asphalt binder using Superpave tests. *Construction and Building Materials, 25*(2), 926-932.

Al-Mansob, R. A., Ismail, A., Alduri, A. N., Azhari, C. H., Karim, M. R., & Yusoff, N. I. M. (2014). Physical and rheological properties of epoxidized natural rubber modified bitumens. *Construction and Building Materials*, *63*, 242-248.

Ali, S. I. A., Ismail, A., Karim, M. R., Yusoff, N. I. M., Al-Mansob, R. A., & Aburkaba, E. (2017). Performance evaluation of Al2O3 nanoparticle-modified asphalt binder. *Road Materials and Pavement Design, 18*(6), 1251-1268.

Amirkhanian, A. N., Xiao, F., & Amirkhanian, S. N. (2010). Evaluation of high temperature rheological characteristics of asphalt binder with carbon nano particles. *Journal of Testing and Evaluation, 39*(4), 583-591.

Aqil, M., Kita, I., Yano, A., & Nishiyama, S. (2007). Analysis and prediction of flow from local source in a river basin using a Neuro-fuzzy modeling tool. *Journal of environmental management, 85*(1), 215-223.

Asadi, S., Hassan, M., Nadiri, A., & Dylla, H. (2014). Artificial intelligence modeling to evaluate field performance of photocatalytic asphalt pavement for ambient air purification. *Environmental Science and Pollution Research, 21*(14), 8847-8857.

Bala, N., Napiah, M., & Kamaruddin, I. (2018). Nanosilica composite asphalt mixtures performance-based design and optimisation using response surface methodology. *International Journal of Pavement Engineering*, 1-12.

Baldo, N., Manthos, E., & Pasetto, M. (2018). Analysis of the Mechanical Behaviour of Asphalt Concretes Using Artificial Neural Networks. *Advances in Civil Engineering, 2018*.

Becker, Y., & Méndez, M. P. (2001). and Yajaira Rodríguez. *VISION TECNOLOGICA, 9*(1), 39.

Bradshaw, J. M. (1997). An introduction to software agents. *Software agents, 5*, 3-46.

Brasileiro, L., Moreno-Navarro, F., Tauste-Martínez, R., Matos, J., & Rubio-Gámez, M. d. C. (2019). Reclaimed Polymers as Asphalt Binder Modifiers for More Sustainable Roads: A Review. *Sustainability, 11*(3), 646.

Brown, S., & Needham, D. (2000). A study of cement modified bitumen emulsion mixtures. *Asphalt Paving Technology*, *69*, 92-121.

Burger, A., Van de Ven, M., Jenkins, K., & Muller, J. (2001). Rheology of polymer modified bitumen: a comparative study of three binders and three binder/filter systems. *SATC 2001*.

Cuadri, A., Partal, P., Navarro, F., García-Morales, M., & Gallegos, C. (2011a). Bitumen chemical modification by thiourea dioxide. *Fuel, 90*(6), 2294-2300.

Cuadri, A., Partal, P., Navarro, F., García-Morales, M., & Gallegos, C. (2011b). Influence of processing temperature on the modification route and rheological properties of thiourea dioxide-modified bitumen. *Energy & Fuels, 25*(9), 4055-4062.

Cüneyt Aydin, A., Tortum, A., & Yavuz, M. (2006). Prediction of concrete elastic modulus using adaptive neuro-fuzzy inference system. *Civil Engineering and Environmental Systems, 23*(4), 295-309.

Dasgupta, D. (1993). An Overview of Artificial Immune Systems and Their Applications. *Springer-Verlag Berlin Heidelberg*.

El-Badawy, S., Abd El-Hakim, R., & Awed, A. (2018). Comparing Artificial Neural Networks with Regression Models for Hot-Mix Asphalt Dynamic Modulus Prediction. *Journal of Materials in Civil Engineering, 30*(7), 04018128.

El-Basyouny, M. M., & Witczak, M. (2005). Calibration of alligator fatigue cracking model for 2002 design guide. *Transportation research record, 1919*(1), 76-86.

Ezzat, H., El-Badawy, S., Gabr, A., Zaki, E.-S. I., & Breakah, T. (2016). Evaluation of asphalt binders modified with nanoclay and nanosilica. *Procedia engineering, 143*, 1260-1267.

Fang, C., Yu, R., Liu, S., & Li, Y. (2013). Nanomaterials applied in asphalt modification: a review. *Journal of Materials Science & Technology, 29*(7), 589-594.

Firouzinia, M., & Shafabakhsh, G. (2018). Investigation of the effect of nano-silica on thermal sensitivity of HMA using artificial neural network. *Construction and Building Materials, 170*, 527-536.

Golestani, B., Nam, B. H., Nejad, F. M., & Fallah, S. (2015). Nanoclay application to asphalt concrete: Characterization of polymer and linear nanocomposite-modified asphalt binder and mixture. *Construction and Building Materials, 91*, 32-38.

Golzar, K., Jalali-Arani, A., & Nematollahi, M. (2012). Statistical investigation on physical–mechanical properties of base and polymer modified bitumen using Artificial Neural Network. *Construction and Building Materials, 37*, 822-831.

Habib, N. Z., Kamaruddin, I., Napiah, M., & Isa, M. T. (2011). Rheological properties of polyethylene and polypropylene modified bitumen. *International Journal Civil and Environmental Engineering, 3*(2), 96-100.

Jahromi, S. G., & Khodaii, A. (2009). Effects of nanoclay on rheological properties of bitumen binder. *Construction and Building Materials, 23*(8), 2894-2904.

Jang, J.-S. R., Sun, C.-T., Mizutani, E., & Ho, Y. (1998). Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence. *Proceedings of the IEEE, 86*(3), 600-603.

Johanneck, L., & Khazanovich, L. (2010). Comprehensive Evaluation of Effect of Climate in Mechanistic–Empirical Pavement Design GuidePredictions. *Transportation research record, 2170*(1), 45-55.

Kar, S., Das, S., & Ghosh, P. K. (2014). Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing, 15*, 243-259.

Khademi, F., Jamal, S. M., Deshpande, N., & Londhe, S. (2016). Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression. *International Journal of Sustainable Built Environment, 5*(2), 355-369.

Kim, Y. R. (2008). *Modeling of asphalt concrete*.

Kishchynskyi, S., Nagaychuk, V., & Bezuglyi, A. (2016). Improving quality and durability of bitumen and asphalt concrete by modification using recycled polyethylene based polymer composition. *Procedia engineering, 143*, 119-127.

Koch, C., Jog, G. M., & Brilakis, I. (2012). Automated pothole distress assessment using asphalt pavement video data. *Journal of Computing in Civil Engineering, 27*(4), 370-378.

Kok, B. V., Yilmaz, M., Sengoz, B., Sengur, A., & Avci, E. (2010). Investigation of complex modulus of base and SBS modified bitumen with artificial neural networks. *Expert Systems with Applications, 37*(12), 7775-7780.

Lamperti, R. (2011). *Rheological and energetic characterization of wax-modified asphalt binders.*

Liu, J., Yan, K., Liu, J., & Zhao, X. (2018). Using artificial neural networks to predict the dynamic modulus of asphalt mixtures containing recycled asphalt shingles. *Journal of Materials in Civil Engineering, 30*(4), 04018051.

Loeber, L., Muller, G., Morel, J., & Sutton, O. (1998). Bitumen in colloid science: a chemical, structural and rheological approach. *Fuel, 77*(13), 1443-1450.

Mirzahosseini, M., Najjar, Y., Alavi, A. H., & Gandomi, A. H. (2013). *ANN-Based prediction model for rutting propensity of asphalt mixtures.* Paper presented at the 92nd Annual Meeting of Transportation Research Board, Washington DC, USA.

Mochinaga, H., Onozuka, S., Kono, F., Ogawa, T., Takahashi, A., & Torigoe, T. (2006). *Properties of Oil sands and Bitumen in Athabasca.* Paper presented at the The Canadian Society of Exploration Geologists CSPG–CSEG–CWLS Convention.

Mohammadi, K., Shamshirband, S., Tong, C. W., Arif, M., Petković, D., & Ch, S. (2015). A new hybrid support vector machine–wavelet transform approach for estimation of horizontal global solar radiation. *Energy Conversion and Management, 92*, 162-171.

Naderpour, H., & Mirrashid, M. (2018). An innovative approach for compressive strength estimation of mortars having calcium inosilicate minerals. *Journal of Building Engineering, 19*, 205-215.

Ozturk, H. I., Saglik, A., Demir, B., & Gungor, A. (2016). *An artificial neural network base prediction model and sensitivity analysis for marshall mix design.* Paper presented at the Proceedings of the 6th Eurasphalt & Eurobitume Congress, Prague, Czech Republic.

Parmar, K. S., & Bhardwaj, R. (2015). River water prediction modeling using neural networks, fuzzy and wavelet coupled model. *Water resources management, 29*(1), 17-33.

Read, J., & Whiteoak, D. (2003). *The shell bitumen handbook*: Thomas Telford.

Robinson, H. (2005). *Polymers in asphalt* (Vol. 15): iSmithers Rapra Publishing.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1985). *Learning internal representations by error propagation*. Retrieved from

Sabadra, V. (2017). Use of Polymer Modified Bitumen in Road Construction. *International Research Journal of Engineering and Technology, 04*(12), 799-801.

Saltan, M., Terzi, S., & Karahancer, S. (2018). Performance analysis of nano modified bitumen and hot mix asphalt. *Construction and Building Materials, 173*, 228-237.

Sarsam, S. I., & Lafta, I. M. (2014). Assessment of Modified-Asphalt Cement Properties. *Journal of Engineering, 20*(6), 1-14.

Sengoz, B., & Isikyakar, G. (2008). Evaluation of the properties and microstructure of SBS and EVA polymer modified bitumen. *Construction and Building Materials, 22*(9), 1897-1905.

Sola, J., & Sevilla, J. (1997). Importance of input data normalization for the application of neural networks to complex industrial problems. *IEEE Transactions on nuclear science, 44*(3), 1464-1468.

Specht, L. P., Khatchatourian, O., Brito, L. A. T., & Ceratti, J. A. P. (2007). Modeling of asphalt-rubber rotational viscosity by statistical analysis and neural networks. *Materials Research, 10*(1), 69-74.

Speight, J. G. (2015). *Asphalt materials science and technology*: Butterworth-Heinemann.

Talpur, N., Salleh, M. N. M., & Hussain, K. (2017). *An investigation of membership functions on performance of ANFIS for solving classification problems.* Paper presented at the IOP Conference Series: Materials Science and Engineering.

Tapkın, S., Çevik, A., & Uşar, Ü. (2009). Accumulated strain prediction of polypropylene modified marshall specimens in repeated creep test using artificial neural networks. *Expert Systems with Applications*, *36*(8), 11186-11197.

Tapkın, S., Çevik, A., & Uşar, Ü. (2010). Prediction of Marshall test results for polypropylene modified dense bituminous mixtures using neural networks. *Expert Systems with Applications, 37*(6), 4660-4670.

User's, F. L. T. T. Guide© COPYRIGHT 1995–2012 The MathWorks: Inc.

Venudharan, V., & Biligiri, K. P. (2017). Heuristic principles to predict the effect of crumb rubber gradation on asphalt binder rutting performance. *Journal of Materials in Civil Engineering*, *29*(8), 04017050.

West, P., & MADISON, W. (2005). Conference. *San Jose, CA.*

Xiao, F., Amirkhanian, A. N., & Amirkhanian, S. N. (2010). Influence of carbon nanoparticles on the rheological characteristics of short-term aged asphalt binders. *Journal of Materials in Civil Engineering, 23*(4), 423-431.

Xiao, F., Amirkhanian, S., & Juang, C. H. (2007). Rutting resistance of rubberized asphalt concrete pavements containing reclaimed asphalt pavement mixtures. *Journal of Materials in Civil Engineering, 19*(6), 475-483.

Xiao, F., Putman, B. J., & Amirkhanian, S. N. (2011). Viscosity prediction of CRM binders using artificial neural network approach. *International Journal of Pavement Engineering, 12*(5), 485-495.

Xu, T., & Huang, X. (2012). Investigation into causes of in-place rutting in asphalt pavement. *Construction and Building Materials, 28*(1), 525-530.

Yang, J., & Tighe, S. (2013). A review of advances of nanotechnology in asphalt mixtures. *Procedia-Social and Behavioral Sciences, 96*, 1269-1276.

Yildirim, Y. (2007). Polymer modified asphalt binders. *Construction and Building Materials, 21*(1), 66-72.

Yilmaz, M., Kok, B. V., Sengoz, B., Sengur, A., & Avci, E. (2011). Investigation of complex modulus of base and EVA modified bitumen with Adaptive-Network-Based Fuzzy Inference System. *Expert Systems with Applications, 38*(1), 969-974.

You, Z., Mills-Beale, J., Foley, J. M., Roy, S., Odegard, G. M., Dai, Q., & Goh, S. W. (2011). Nanoclay-modified asphalt materials: Preparation and characterization. *Construction and Building Materials*, *25*(2), 1072-1078.

Yusoff, N. I. M., Breem, A. A. S., Alattug, H. N., Hamim, A., & Ahmad, J. (2014). The effects of moisture susceptibility and ageing conditions on nano-silica/polymer-modified asphalt mixtures. *Construction and Building Materials*, *72*, 139-147.

Zhu, J., Birgisson, B., & Kringos, N. (2014). Polymer modification of bitumen: Advances and challenges. *European Polymer Journal, 54*, 18-38.

Ziari, H., Amini, A., Goli, A., & Mirzaeiyan, D. (2018). Predicting rutting performance of carbon nano tube (CNT) asphalt binders using regression models and neural networks. *Construction and Building Materials*, *160*, 415-426.

APPENDIX 1

Penetration	Softening point	Binder Type	Tempretuee in C	frequency in Hz	Strain in pa	|G*| in Pa
82	46	BASE ASPHLAT	46	0.159	1.2	407
82	46	BASE ASPHLAT	46	0.2	1.2	525.3
82	46	BASE ASPHLAT	46	0.5	1.2	953.8
82	46	BASE ASPHLAT	46	1.592	1.2	1787
82	46	BASE ASPHLAT	46	2	1.2	1796
82	46	BASE ASPHLAT	46	3	1.2	2430
82	46	BASE ASPHLAT	46	5	1.2	3662
82	46	BASE ASPHLAT	46	10	1.2	6538
82	46	BASE ASPHLAT	46	15.92	1.2	8616
82	46	BASE ASPHLAT	52	0.159	1.2	234.6
82	46	BASE ASPHLAT	52	0.2	1.2	296.2
82	46	BASE ASPHLAT	52	0.5	1.2	709.8
82	46	BASE ASPHLAT	52	1.592	1.2	2110
82	46	BASE ASPHLAT	52	2	1.2	2537
82	46	BASE ASPHLAT	52	3	1.2	3561
82	46	BASE ASPHLAT	52	5	1.2	3426
82	46	BASE ASPHLAT	52	10	1.2	5106
82	46	BASE ASPHLAT	52	15.92	1.2	6731
82	46	BASE ASPHLAT	58	0.159	1.2	113.9
82	46	BASE ASPHLAT	58	0.2	1.2	143.6
82	46	BASE ASPHLAT	58	0.5	1.2	352.8
82	46	BASE ASPHLAT	58	1.592	1.2	1070
82	46	BASE ASPHLAT	58	2	1.2	1317
82	46	BASE ASPHLAT	58	3	1.2	1926
82	46	BASE ASPHLAT	58	5	1.2	3064
82	46	BASE ASPHLAT	58	10	1.2	3816
82	46	BASE ASPHLAT	58	15.92	1.2	5484
82	46	BASE ASPHLAT	64	0.159	1.2	57.26
82	46	BASE ASPHLAT	64	0.2	1.2	72.11
82	46	BASE ASPHLAT	64	0.5	1.2	178.3
82	46	BASE ASPHLAT	64	1.592	1.2	554.5
82	46	BASE ASPHLAT	64	2	1.2	691.8
82	46	BASE ASPHLAT	64	3	1.2	1024
82	46	BASE ASPHLAT	64	5	1.2	1668
82	46	BASE ASPHLAT	64	10	1.2	3201
82	46	BASE ASPHLAT	64	15.92	1.2	4831
82	46	BASE ASPHLAT	70	0.159	1.2	30.41
82	46	BASE ASPHLAT	70	0.2	1.2	38.49
82	46	BASE ASPHLAT	70	0.5	1.2	95.36
82	46	BASE ASPHLAT	70	1.592	1.2	299.2
82	46	BASE ASPHLAT	70	2	1.2	375.3
82	46	BASE ASPHLAT	70	3	1.2	559.2
82	46	BASE ASPHLAT	70	5	1.2	918.2
82	46	BASE ASPHLAT	70	10	1.2	1773
82	46	BASE ASPHLAT	70	15.92	1.2	2723
82	46	BASE ASPHLAT	76	0.159	1.2	17.58
82	46	BASE ASPHLAT	76	0.2	1.2	21.91
82	46	BASE ASPHLAT	76	0.5	1.2	54.05
82	46	BASE ASPHLAT	76	1.592	1.2	169.4
82	46	BASE ASPHLAT	76	2	1.2	212.8
82	46	BASE ASPHLAT	76	3	1.2	318.8
82	46	BASE ASPHLAT	76	5	1.2	528.8
82	46	BASE ASPHLAT	76	10	1.2	1035
82	46	BASE ASPHLAT	76	15.92	1.2	1631
82	46	BASE ASPHLAT	82	0.159	1.2	10.86
82	46	BASE ASPHLAT	82	0.2	1.2	13.54
82	46	BASE ASPHLAT	82	0.5	1.2	33.05
82	46	BASE ASPHLAT	82	1.592	1.2	103.2
82	46	BASE ASPHLAT	82	2	1.2	129.8
82	46	BASE ASPHLAT	82	3	1.2	194.5
82	46	BASE ASPHLAT	82	5	1.2	323.3
82	46	BASE ASPHLAT	82	10	1.2	644.6
82	46	BASE ASPHLAT	82	15.92	1.2	1029
74	50	5% ASA	46	0.159	1.2	854.1
74	50	5% ASA	46	0.2	1.2	1049
74	50	5% ASA	46	0.5	1.2	2355
74	50	5% ASA	46	1.592	1.2	6834
74	50	5% ASA	46	2	1.2	8984
74	50	5% ASA	46	3	1.2	9511
74	50	5% ASA	46	5	1.2	13780
74	50	5% ASA	46	10	1.2	22820
74	50	5% ASA	46	15.92	1.2	33960
74	50	5% ASA	52	0.159	1.2	367.1
74	50	5% ASA	52	0.2	1.2	460.2
74	50	5% ASA	52	0.5	1.2	1112
74	50	5% ASA	52	1.592	1.2	3239
74	50	5% ASA	52	2	1.2	3830
74	50	5% ASA	52	3	1.2	5397
74	50	5% ASA	52	5	1.2	6422
74	50	5% ASA	52	10	1.2	11090
74	50	5% ASA	52	15.92	1.2	19110
74	50	5% ASA	58	0.159	1.2	163.8
74	50	5% ASA	58	0.2	1.2	205.7
74	50	5% ASA	58	0.5	1.2	502.4
74	50	5% ASA	58	1.592	1.2	1521
74	50	5% ASA	58	2	1.2	1871
74	50	5% ASA	58	3	1.2	2733
74	50	5% ASA	58	5	1.2	4346
74	50	5% ASA	58	10	1.2	7058
74	50	5% ASA	58	15.92	1.2	11390
74	50	5% ASA	64	0.159	1.2	83.26
74	50	5% ASA	64	0.2	1.2	105.1
74	50	5% ASA	64	0.5	1.2	258.6
74	50	5% ASA	64	1.592	1.2	798.3
74	50	5% ASA	64	2	1.2	993.4
74	50	5% ASA	64	3	1.2	1465
74	50	5% ASA	64	5	1.2	2376
74	50	5% ASA	64	10	1.2	4553
74	50	5% ASA	64	15.92	1.2	6784
74	50	5% ASA	70	0.159	1.2	43.64
74	50	5% ASA	70	0.2	1.2	55.03
74	50	5% ASA	70	0.5	1.2	135.7
74	50	5% ASA	70	1.592	1.2	424.8
74	50	5% ASA	70	2	1.2	530
74	50	5% ASA	70	3	1.2	786.3
74	50	5% ASA	70	5	1.2	1283
74	50	5% ASA	70	10	1.2	2486
74	50	5% ASA	70	15.92	1.2	3766
74	50	5% ASA	76	0.159	1.2	24.35
74	50	5% ASA	76	0.2	1.2	30.54
74	50	5% ASA	76	0.5	1.2	75.37
74	50	5% ASA	76	1.592	1.2	235.8
74	50	5% ASA	76	2	1.2	295.7
74	50	5% ASA	76	3	1.2	440.3
74	50	5% ASA	76	5	1.2	725.6
74	50	5% ASA	76	10	1.2	1405
74	50	5% ASA	76	15.92	1.2	2188
74	50	5% ASA	82	0.159	1.2	14.29
74	50	5% ASA	82	0.2	1.2	17.96
74	50	5% ASA	82	0.5	1.2	43.93
74	50	5% ASA	82	1.592	1.2	137
74	50	5% ASA	82	2	1.2	172.3
74	50	5% ASA	82	3	1.2	257.7
74	50	5% ASA	82	5	1.2	425.8
74	50	5% ASA	82	10	1.2	832.7
74	50	5% ASA	82	15.92	1.2	1318

66.4	56	3% ASA-COPPER	46	0.1592	1.2	1842.5
66.4	56	3% ASA-COPPER	46	0.2	1.2	2245.5
66.4	56	3% ASA-COPPER	46	0.5	1.2	5193.1
66.4	56	3% ASA-COPPER	46	1.592	1.2	11257.5
66.4	56	3% ASA-COPPER	46	2	1.2	12990.4
66.4	56	3% ASA-COPPER	46	3	1.2	17676.0
66.4	56	3% ASA-COPPER	46	5	1.2	25076.3
66.4	56	3% ASA-COPPER	46	10	1.2	50244.7
66.4	56	3% ASA-COPPER	46	15.92	1.2	80819.3
66.4	56	3% ASA-COPPER	52	0.1592	1.2	743.4
66.4	56	3% ASA-COPPER	52	0.2	1.2	927.3
66.4	56	3% ASA-COPPER	52	0.5	1.2	2226.1
66.4	56	3% ASA-COPPER	52	1.592	1.2	6391.5
66.4	56	3% ASA-COPPER	52	2	1.2	7559.1
66.4	56	3% ASA-COPPER	52	3	1.2	8956.3
66.4	56	3% ASA-COPPER	52	5	1.2	11218.4
66.4	56	3% ASA-COPPER	52	10	1.2	21706.0
66.4	56	3% ASA-COPPER	52	15.92	1.2	33373.9
66.4	56	3% ASA-COPPER	58	0.1592	1.2	326.6
66.4	56	3% ASA-COPPER	58	0.2	1.2	411.0
66.4	56	3% ASA-COPPER	58	0.5	1.2	1004.0
66.4	56	3% ASA-COPPER	58	1.592	1.2	3020.4
66.4	56	3% ASA-COPPER	58	2	1.2	3715.8
66.4	56	3% ASA-COPPER	58	3	1.2	5020.4
66.4	56	3% ASA-COPPER	58	5	1.2	7532.7
66.4	56	3% ASA-COPPER	58	10	1.2	13430.0
66.4	56	3% ASA-COPPER	58	15.92	1.2	20453.2
66.4	56	3% ASA-COPPER	64	0.1592	1.2	154.4
66.4	56	3% ASA-COPPER	64	0.2	1.2	194.3
66.4	56	3% ASA-COPPER	64	0.5	1.2	480.5
66.4	56	3% ASA-COPPER	64	1.592	1.2	1479.1
66.4	56	3% ASA-COPPER	64	2	1.2	1841.1
66.4	56	3% ASA-COPPER	64	3	1.2	2713.7
66.4	56	3% ASA-COPPER	64	5	1.2	4367.6
66.4	56	3% ASA-COPPER	64	10	1.2	7410.6
66.4	56	3% ASA-COPPER	64	15.92	1.2	11585.6
66.4	56	3% ASA-COPPER	70	0.1592	1.2	74.8
66.4	56	3% ASA-COPPER	70	0.2	1.2	94.4
66.4	56	3% ASA-COPPER	70	0.5	1.2	234.7
66.4	56	3% ASA-COPPER	70	1.592	1.2	734.2
66.4	56	3% ASA-COPPER	70	2	1.2	917.5
66.4	56	3% ASA-COPPER	70	3	1.2	1362.3
66.4	56	3% ASA-COPPER	70	5	1.2	2231.6
66.4	56	3% ASA-COPPER	70	10	1.2	4325.3
66.4	56	3% ASA-COPPER	70	15.92	1.2	6264.2
66.4	56	3% ASA-COPPER	76	0.1592	1.2	41.1
66.4	56	3% ASA-COPPER	76	0.2	1.2	51.7
66.4	56	3% ASA-COPPER	76	0.5	1.2	128.5
66.4	56	3% ASA-COPPER	76	1.592	1.2	404.7
66.4	56	3% ASA-COPPER	76	2	1.2	506.9
66.4	56	3% ASA-COPPER	76	3	1.2	754.1
66.4	56	3% ASA-COPPER	76	5	1.2	1240.6
66.4	56	3% ASA-COPPER	76	10	1.2	2432.6
66.4	56	3% ASA-COPPER	76	15.92	1.2	3743.5
66.4	56	3% ASA-COPPER	82	0.1592	1.2	23.0
66.4	56	3% ASA-COPPER	82	0.2	1.2	28.8
66.4	56	3% ASA-COPPER	82	0.5	1.2	71.5
66.4	56	3% ASA-COPPER	82	1.592	1.2	225.8
66.4	56	3% ASA-COPPER	82	2	1.2	283.6
66.4	56	3% ASA-COPPER	82	3	1.2	424.1
66.4	56	3% ASA-COPPER	82	5	1.2	701.8
66.4	56	3% ASA-COPPER	82	10	1.2	1370.2
66.4	56	3% ASA-COPPER	82	15.92	1.2	2156.4

75.3	55	3% ASA-KAL	46	0.159	1.2	2115
75.3	55	3% ASA-KAL	46	0.2	1.2	2611
75.3	55	3% ASA-KAL	46	0.5	1.2	6011
75.3	55	3% ASA-KAL	46	1.592	1.2	17220
75.3	55	3% ASA-KAL	46	2	1.2	20190
75.3	55	3% ASA-KAL	46	3	1.2	27500
75.3	55	3% ASA-KAL	46	5	1.2	36880
75.3	55	3% ASA-KAL	46	10	1.2	75220
75.3	55	3% ASA-KAL	46	15.92	1.2	117800
75.3	55	3% ASA-KAL	52	0.159	1.2	852.3
75.3	55	3% ASA-KAL	52	0.2	1.2	1067
75.3	55	3% ASA-KAL	52	0.5	1.2	2563
75.3	55	3% ASA-KAL	52	1.592	1.2	7538
75.3	55	3% ASA-KAL	52	2	1.2	9064
75.3	55	3% ASA-KAL	52	3	1.2	12940
75.3	55	3% ASA-KAL	52	5	1.2	19690
75.3	55	3% ASA-KAL	52	10	1.2	37850
75.3	55	3% ASA-KAL	52	15.92	1.2	60920
75.3	55	3% ASA-KAL	58	0.159	1.2	371.6
75.3	55	3% ASA-KAL	58	0.2	1.2	467.9
75.3	55	3% ASA-KAL	58	0.5	1.2	1137
75.3	55	3% ASA-KAL	58	1.592	1.2	3445
75.3	55	3% ASA-KAL	58	2	1.2	4275
75.3	55	3% ASA-KAL	58	3	1.2	6263
75.3	55	3% ASA-KAL	58	5	1.2	10050
75.3	55	3% ASA-KAL	58	10	1.2	19170
75.3	55	3% ASA-KAL	58	15.92	1.2	30400
75.3	55	3% ASA-KAL	64	0.159	1.2	173.8
75.3	55	3% ASA-KAL	64	0.2	1.2	218.3
75.3	55	3% ASA-KAL	64	0.5	1.2	535.9
75.3	55	3% ASA-KAL	64	1.592	1.2	1650
75.3	55	3% ASA-KAL	64	2	1.2	2051
75.3	55	3% ASA-KAL	64	3	1.2	3030
75.3	55	3% ASA-KAL	64	5	1.2	4919
75.3	55	3% ASA-KAL	64	10	1.2	9421
75.3	55	3% ASA-KAL	64	15.92	1.2	14970
75.3	55	3% ASA-KAL	70	0.159	1.2	84.77
75.3	55	3% ASA-KAL	70	0.2	1.2	107.3
75.3	55	3% ASA-KAL	70	0.5	1.2	266.1
75.3	55	3% ASA-KAL	70	1.592	1.2	825.8
75.3	55	3% ASA-KAL	70	2	1.2	1034
75.3	55	3% ASA-KAL	70	3	1.2	1536
75.3	55	3% ASA-KAL	70	5	1.2	2516
75.3	55	3% ASA-KAL	70	10	1.2	4919
75.3	55	3% ASA-KAL	70	15.92	1.2	7428
75.3	55	3% ASA-KAL	76	0.159	1.2	45.2
75.3	55	3% ASA-KAL	76	0.2	1.2	56.79
75.3	55	3% ASA-KAL	76	0.5	1.2	141.1
75.3	55	3% ASA-KAL	76	1.592	1.2	441.4
75.3	55	3% ASA-KAL	76	2	1.2	551.4
75.3	55	3% ASA-KAL	76	3	1.2	820.3
75.3	55	3% ASA-KAL	76	5	1.2	1355
75.3	55	3% ASA-KAL	76	10	1.2	2649
75.3	55	3% ASA-KAL	76	15.92	1.2	4109
75.3	55	3% ASA-KAL	82	0.159	1.2	25.2
75.3	55	3% ASA-KAL	82	0.2	1.2	31.59
75.3	55	3% ASA-KAL	82	0.5	1.2	78.68
75.3	55	3% ASA-KAL	82	1.592	1.2	247.1
75.3	55	3% ASA-KAL	82	2	1.2	309.4
75.3	55	3% ASA-KAL	82	3	1.2	460.9
75.3	55	3% ASA-KAL	82	5	1.2	759.8
75.3	55	3% ASA-KAL	82	10	1.2	1490
75.3	55	3% ASA-KAL	82	15.92	1.2	2344
75.3	55	3% ASA-KAL	82	15.92	1.2	2344

69.1	55	5% ASA-COPPER	46	0.159	1.2	337.5
69.1	55	5% ASA-COPPER	46	0.2	1.2	422.3
69.1	55	5% ASA-COPPER	46	0.5	1.2	868
69.1	55	5% ASA-COPPER	46	1.592	1.2	2369
69.1	55	5% ASA-COPPER	46	2	1.2	2657
69.1	55	5% ASA-COPPER	46	3	1.2	3241
69.1	55	5% ASA-COPPER	46	5	1.2	4533
69.1	55	5% ASA-COPPER	46	10	1.2	7235
69.1	55	5% ASA-COPPER	46	15.92	1.2	10840
69.1	55	5% ASA-COPPER	52	0.159	1.2	341.2
69.1	55	5% ASA-COPPER	52	0.2	1.2	435
69.1	55	5% ASA-COPPER	52	0.5	1.2	1018
69.1	55	5% ASA-COPPER	52	1.592	1.2	2163
69.1	55	5% ASA-COPPER	52	2	1.2	1996
69.1	55	5% ASA-COPPER	52	3	1.2	2658
69.1	55	5% ASA-COPPER	52	5	1.2	3897
69.1	55	5% ASA-COPPER	52	10	1.2	6654
69.1	55	5% ASA-COPPER	52	15.92	1.2	8451
69.1	55	5% ASA-COPPER	58	0.159	1.2	191.8
69.1	55	5% ASA-COPPER	58	0.2	1.2	244
69.1	55	5% ASA-COPPER	58	0.5	1.2	595.5
69.1	55	5% ASA-COPPER	58	1.592	1.2	1749
69.1	55	5% ASA-COPPER	58	2	1.2	2101
69.1	55	5% ASA-COPPER	58	3	1.2	3004
69.1	55	5% ASA-COPPER	58	5	1.2	4588
69.1	55	5% ASA-COPPER	58	10	1.2	6607
69.1	55	5% ASA-COPPER	58	15.92	1.2	10400
69.1	55	5% ASA-COPPER	64	0.159	1.2	101.9
69.1	55	5% ASA-COPPER	64	0.2	1.2	129.2
69.1	55	5% ASA-COPPER	64	0.5	1.2	319.2
69.1	55	5% ASA-COPPER	64	1.592	1.2	977.3
69.1	55	5% ASA-COPPER	64	2	1.2	1208
69.1	55	5% ASA-COPPER	64	3	1.2	1775
69.1	55	5% ASA-COPPER	64	5	1.2	2863
69.1	55	5% ASA-COPPER	64	10	1.2	5394
69.1	55	5% ASA-COPPER	64	15.92	1.2	6477
69.1	55	5% ASA-COPPER	70	0.159	1.2	53.5
69.1	55	5% ASA-COPPER	70	0.2	1.2	67.49
69.1	55	5% ASA-COPPER	70	0.5	1.2	167
69.1	55	5% ASA-COPPER	70	1.592	1.2	522.4
69.1	55	5% ASA-COPPER	70	2	1.2	651.5
69.1	55	5% ASA-COPPER	70	3	1.2	964.2
69.1	55	5% ASA-COPPER	70	5	1.2	1571
69.1	55	5% ASA-COPPER	70	10	1.2	3016
69.1	55	5% ASA-COPPER	70	15.92	1.2	4592
69.1	55	5% ASA-COPPER	76	0.159	1.2	29.36
69.1	55	5% ASA-COPPER	76	0.2	1.2	36.97
69.1	55	5% ASA-COPPER	76	0.5	1.2	91.38
69.1	55	5% ASA-COPPER	76	1.592	1.2	287.5
69.1	55	5% ASA-COPPER	76	2	1.2	360.4
69.1	55	5% ASA-COPPER	76	3	1.2	537
69.1	55	5% ASA-COPPER	76	5	1.2	881.6
69.1	55	5% ASA-COPPER	76	10	1.2	1696
69.1	55	5% ASA-COPPER	76	15.92	1.2	2629
69.1	55	5% ASA-COPPER	82	0.159	1.2	17.09
69.1	55	5% ASA-COPPER	82	0.2	1.2	21.39
69.1	55	5% ASA-COPPER	82	0.5	1.2	52.65
69.1	55	5% ASA-COPPER	82	1.592	1.2	166.6
69.1	55	5% ASA-COPPER	82	2	1.2	209.9
69.1	55	5% ASA-COPPER	82	3	1.2	313.5
69.1	55	5% ASA-COPPER	82	5	1.2	518.2
69.1	55	5% ASA-COPPER	82	10	1.2	1028
69.1	55	5% ASA-COPPER	82	15.92	1.2	1589

76.9	53	5% ASA-KAL	46	0.159	1.2	920.9
76.9	53	5% ASA-KAL	46	0.2	1.2	1142
76.9	53	5% ASA-KAL	46	0.5	1.2	2607
76.9	53	5% ASA-KAL	46	1.592	1.2	6473
76.9	53	5% ASA-KAL	46	2	1.2	7547
76.9	53	5% ASA-KAL	46	3	1.2	10470
76.9	53	5% ASA-KAL	46	5	1.2	15370
76.9	53	5% ASA-KAL	46	10	1.2	26710
76.9	53	5% ASA-KAL	46	15.92	1.2	43000
76.9	53	5% ASA-KAL	52	0.159	1.2	455.2
76.9	53	5% ASA-KAL	52	0.2	1.2	572
76.9	53	5% ASA-KAL	52	0.5	1.2	1374
76.9	53	5% ASA-KAL	52	1.592	1.2	3961
76.9	53	5% ASA-KAL	52	2	1.2	4654
76.9	53	5% ASA-KAL	52	3	1.2	6498
76.9	53	5% ASA-KAL	52	5	1.2	9690
76.9	53	5% ASA-KAL	52	10	1.2	16020
76.9	53	5% ASA-KAL	52	15.92	1.2	25790
76.9	53	5% ASA-KAL	58	0.159	1.2	209.7
76.9	53	5% ASA-KAL	58	0.2	1.2	264.7
76.9	53	5% ASA-KAL	58	0.5	1.2	646.2
76.9	53	5% ASA-KAL	58	1.592	1.2	1957
76.9	53	5% ASA-KAL	58	2	1.2	2396
76.9	53	5% ASA-KAL	58	3	1.2	3495
76.9	53	5% ASA-KAL	58	5	1.2	5545
76.9	53	5% ASA-KAL	58	10	1.2	9619
76.9	53	5% ASA-KAL	58	15.92	1.2	15530
76.9	53	5% ASA-KAL	64	0.159	1.2	100
76.9	53	5% ASA-KAL	64	0.2	1.2	126
76.9	53	5% ASA-KAL	64	0.5	1.2	310.2
76.9	53	5% ASA-KAL	64	1.592	1.2	958.4
76.9	53	5% ASA-KAL	64	2	1.2	1194
76.9	53	5% ASA-KAL	64	3	1.2	1767
76.9	53	5% ASA-KAL	64	5	1.2	2875
76.9	53	5% ASA-KAL	64	10	1.2	5541
76.9	53	5% ASA-KAL	64	15.92	1.2	7541
76.9	53	5% ASA-KAL	70	0.159	1.2	51.48
76.9	53	5% ASA-KAL	70	0.2	1.2	64.94
76.9	53	5% ASA-KAL	70	0.5	1.2	161.1
76.9	53	5% ASA-KAL	70	1.592	1.2	502.5
76.9	53	5% ASA-KAL	70	2	1.2	628.4
76.9	53	5% ASA-KAL	70	3	1.2	933.5
76.9	53	5% ASA-KAL	70	5	1.2	1527
76.9	53	5% ASA-KAL	70	10	1.2	2961
76.9	53	5% ASA-KAL	70	15.92	1.2	4576
76.9	53	5% ASA-KAL	76	0.159	1.2	28.99
76.9	53	5% ASA-KAL	76	0.2	1.2	36.51
76.9	53	5% ASA-KAL	76	0.5	1.2	89.88
76.9	53	5% ASA-KAL	76	1.592	1.2	282.3
76.9	53	5% ASA-KAL	76	2	1.2	353.7
76.9	53	5% ASA-KAL	76	3	1.2	527.3
76.9	53	5% ASA-KAL	76	5	1.2	868
76.9	53	5% ASA-KAL	76	10	1.2	1682
76.9	53	5% ASA-KAL	76	15.92	1.2	2630
76.9	53	5% ASA-KAL	82	0.159	1.2	16.85
76.9	53	5% ASA-KAL	82	0.2	1.2	21.07
76.9	53	5% ASA-KAL	82	0.5	1.2	51.7
76.9	53	5% ASA-KAL	82	1.592	1.2	162.4
76.9	53	5% ASA-KAL	82	2	1.2	203.5
76.9	53	5% ASA-KAL	82	3	1.2	304.3
76.9	53	5% ASA-KAL	82	5	1.2	505.8
76.9	53	5% ASA-KAL	82	10	1.2	986.8
76.9	53	5% ASA-KAL	82	15.92	1.2	1554
76.9	53	5% ASA-KAL	82	10	1.2	986.8
76.9	53	5% ASA-KAL	82	15.92	1.2	1554