# Predicting Fatigue Performance of Hot Mix Asphalt using Artificial Neural Networks

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Developing predictive models for fatigue performance is a complex process and can depend on variables including material properties, test conditions and sample geometry. Several models have been developed in this regard; some of these are regression models and are related to mechanistic properties in addition to volumetric properties. In this work, a computational model, based on artificial neural networks (ANNs), is used to predict the fatigue performance of hot mix asphalt (HMA) tested in a dynamic shear rheometer (DSR) technique. Fatigue performance was evaluated according to three approaches: traditional, energy ratio and dissipated pseudo strain energy. For predicting fatigue performance, two types of ANN models were developed: dependent test mode, i.e. based on controlled test modes, and independent test modes, i.e. irrespective of controlled test modes; using fundamental parameters e.g. stiffness modulus, phase angle and volumetric properties. In this work, limestone (L) and granite (G) aggregates were used with two binder grades (40/60 and 160/220) to prepare four mixtures with two different gradations: gap-graded hot rolled asphalt (HRA) and continuously graded dense bitumen macadam (DBM). The results revealed an excellent correlation between the predicted and experimental data. It was found that the prediction accuracy of the strain test mode was better than the stress test mode.

**Keywords**: Fatigue performance, artificial neural network, hot mix asphalt, DSR technique.

## 1. Introduction

Hot mix asphalt (HMA) is a composite material with compounds from different scales: coarse and fine aggregates, filler and bitumen as a binder. Because of its composite nature (in addition to other factors such as environmental, test conditions and the properties of the material itself), the performance behaviour of HMA, e.g. fatigue, rutting and cracking, is complex and difficult to predict (You and Buttlar, 2004, Xiao *et al.*, 2007). This complex behaviour arises because of the response of these components under loading – the stiffness of the aggregates is several times higher than that of the binder and deformation in the binder leads to non-linear behaviour in the HMA. In addition, rotation, slippage and interaction between aggregates all contribute to this non-linear behaviour (Masad and Somadevan, 2002, Huang *et al.*, 2007).

### *1.1. Regression Models for Fatigue Life*

Despite the complex behaviour of HMA, several attempts have been made to develop regression models which predict its performance. To the best of the author's knowledge the earliest model, introduced during the 1960s, was based on the relationship between HMA fatigue life (in terms of number of cycles) and horizontal tensile strain and tensile stress at the bottom of the asphalt layer (Monismith *et al.*, 1961, Pell, 1962). Later, studies were extended in order to take into account mix properties (represented by the stiffness modulus (Monismith *et al.*, 1985, Monismith, 1969)).

Extensive efforts were made to develop new regression models to predict the fatigue life of HMA based on large experimental studies; in these cases several variables related to the mix properties were represented in the models in order to take into account the variability of the mix properties and test conditions. For example, Bonnaure *et al.* (1980) developed regression models to predict the fatigue life of HMA for controlled strain and stress test modes. These models were more comprehensive: volumetric binder content ($V_b$) and temperature effects presented by the penetration index (PI) were included in these models (in addition to the stiffness modulus). The Shell International Petroleum Company (1978) also developed a model to predict the fatigue life of HMA, but in this case the volume of the binder ($V_b$) was included in the model (Shell, 1978). The Asphalt Institute developed a relationship similar to Shell's model, except voids filled with binder (VFB) were used in this model instead of $V_b$ (Shook *et al.*, 1982). The Energy approach was used in several studies to predict the fatigue performance of HMA (Van Dijk and Visser, 1977, Tayebali *et al.*, 1992, Rowe, 1993, Ghuzlan and Carpenter, 2006). This approach is based on the hypothesis that the amount of energy dissipated is proportional to the number of cycles during cyclic loading. Despite their continued use, efforts are still being made to improve the performance of regression models by adding new parameters or fine tuning existing ones. There are still, however, problems with regard to the goodness of fit (quality) of these regression models, which is evaluated as the correlation between actual and predicted values using the determination coefficient ($R^2$). Since the 1980s, a mathematical technique called artificial neural networks (ANNs) has been used widely to improve the prediction performance of a wide variety of models and the outcomes have often been good in terms of closeness of fit and the high correlation between actual and predicted results (Adeli, 2001). In the current paper, ANNs are used to develop models for predicting the fatigue life of HMA based on the mechanical and volumetric properties. Two categories of models were developed: the first was based on test modes (strain and stress) and while the second could be applied irrespective of test mode.

### *1.2. Artificial Neural Networks (ANNs)*

Artificial neural networks (ANNs) are computational models that are (loosely) based on the structure and functions of the central nervous system (Adeli, 2001, Priddy and Keller, 2005). ANNs consist of a large class of different architectures – multilayer neural networks are among the most widely used and consist of: input layers, hidden layers and output layers. In the hidden layers, there are a number of nodes called neurons, which represent the processing elements of the ANN. Each neuron takes a set of weights as an input to a transfer function, which produces a scalar output (as illustrated in Figure 1). The outputs of the three layers of the ANN in Figure 1 are calculated as in Equation (1) (Priddy and Keller, 2005):

$$Y = \theta\{\beta + \textstyle\sum_{j=1}^{n}[V_j . \theta_j(b_j + \sum_{i=1}^{k} X_i W_{ij})]\} \qquad (1)$$

where: $\beta$ is the output bias; $W_{ij}$ is the weight connection between neuron $j$ in the hidden layers and input layers $i$; $V_j$ is the weight connection between neuron $j$ in the hidden layers and the output layer; $b_j$ is the bias at neuron $j$ of the hidden layers; $\theta$ is the transfer function from hidden layers to the output layer; $\theta_j$ is the transfer function from the input layers to hidden layers and $n$ is the number of neurons in the hidden layer; and $k$ is the number of inputs.

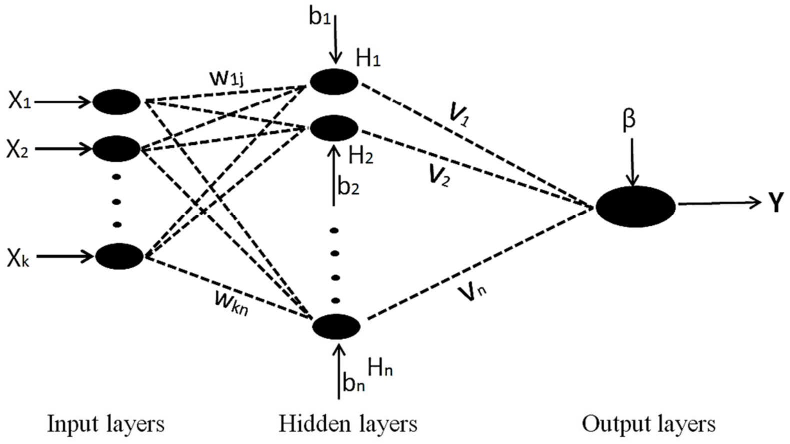


Figure 1: Three layered neural network architecture.

In ANNs, the back propagation method is often used to train the network's weights and biases (Priddy and Keller, 2005). The most common transfer function is the sigmoid function; Equation (2) represents the formula of a sigmoidal logistic function;

$$\theta(u) = \frac{1}{1+e^{-u}} \tag{2}$$

This function has nice mathematical properties such as continuity and differentiability that are very important during training. The working principle of ANNs is based on supervised learning; where, a simple error back-propagation (BP) training algorithm is used to train the neural networks. During the training, information is propagated forward through the neural network. The output response is compared to the observed outputs (or target) data. The error is then computed and propagated backward through the network neurons and used to make adjustments in the weights and biases (Adeli, 2001, Priddy and Keller, 2005, Haykin, 1999). This method of training is used throughout the current paper.

### *1.3. Utilisation of ANNs*

ANNs have been used successfully by researchers for prediction, classification and noise reduction in different disciplines of civil engineering; more details about the use of ANNs in civil engineering are available in the review paper by Adeli (2001). There are numerous studies which use ANNs to enhance predictive models for HMA performance. For example, Xiao *et al.* (2009) used a three-layered ANN to predict the fatigue life of rubberized asphalt concrete (RAC) and compared this with two regression models: the strain-dependent model and the energy-dependent model (Xiao, 2009). These two models led to a poor fit between the predicted and actual result, with low determination coefficients and high coefficients of variation (CoV). At the same time, the same independent variables for the two regression models have been used as inputs to an ANN, to predict the fatigue life of RAC. This led to a high correlation between the actual and predicted results; however, there are no details given about the numbers of neurons in the hidden layers and the data size was limited. Celyan *et al.* (2009) used ANNs with two hidden layers (20 neurons in each) to enhance the accuracy of the Witczak 1999–2006 models (Andrei *et al.*, 1999, Bari and Witczak, 2006) for predicting the dynamic modulus, |E*|, of HMA.

In the study, the same input parameters as used by Witczak were used as inputs to the ANN. The study demonstrated a significant improvement in the ANN predictive model compared to other regression models: Witczak-1999 and Witczak-2006 (Ceylan *et al.*, 2009). Subsequently, an ANN with four layers (input–hidden–hidden–output) was used to predict the stiffness modulus |E*| of HMA (Ceylan, 2008). The same input parameters as used in an empirical model - called the Hirsch model - were used. The ANN model showed a remarkably high performance in predicting the stiffness modulus of HMA compared with the Hirsch model.

## 2. Objectives of Study

The following objectives have been determined for modelling using an ANN:

1. To predict the fatigue performance of asphalt mixes tested in DSR and evaluated according to three approaches: the traditional approach (TA), the energy ratio approach (ER) and the fatigue index ($FI^R$) approach. Fatigue test parameters such as initial stiffness modulus, initial phase angle, shear strain amplitude, shear stress amplitude and relaxation test coefficients ($G_1$, m); in addition to volumetric properties (bulk density and air voids), were nominated as input parameters for the ANN. In this study, fatigue test parameters and volumetric properties are referred to as 'fundamental parameters'.
2. Develop ANN models for predicting the fatigue performance of HMA, irrespective of fatigue test modes.
3. Conduct a bias analysis of the resulting ANN models.

## 3. Materials and Experimental Work

Experimental work includes performing fatigue tests using DSR instruments applied on HMA samples. In this work, DSR cylindrical samples (12 mm in diameter and 50 mm in height) were produced from two kinds of mixes. Hot rolled asphalt (HRA) and dense bitumen macadam (DBM) samples were prepared in the laboratory using two types of aggregate: limestone (L) and granite (G), with two binders: 40/60 and 160/220 pen grades, according to British Standards recipes (BS 4987-1, 2005, BS 597-1, 2005, BS PD 6691, 2010). The DSR samples were produced by coring beams cut from roller-compacted slabs for HMA prepared in the lab. The experimental work included performing fatigue tests using the DSR technique in stress and strain modes, using an approach that was developed and presented in (Ahmed and Khalid, 2015, Ahmed, 2016). Table 1 shows relevant details and test conditions.

**Table 1** Mix ID, material details and test conditions.

| Mix ID | Mixes properties | | | | Test Conditions | |
|---|---|---|---|---|---|---|
| | Grade mm | Content % | $G_{bulk}$ Mg/m$^3$ | Air voids % | Strain (%) | Stress KPa |
| DBM-L | 160/220 | 5.2 | 2.374 | 4.9 | 0.30 | 150 |
| DBM-G | 160/220 | 5.2 | 2.290 | 7.5 | 0.30 | 150 |
| HRA-L | 40/60 | 7.8 | 2.343 | 2.2 | 0.25 | 250 |
| HRA-G | 40/60 | 7.8 | 2.298 | 4.0 | 0.25 | 400 |

## 4. Results and Discussion

In this study, fatigue performance was defined using three approaches:

1. The traditional approach (TA) defines fatigue life ($N_f$) as the number of cycles at which, respectively, 50% and 10% of the initial stiffness modulus occurs (Tayebali *et al.*, 1992, Rowe, 1993, Kim *et al.*, 2002, Ghuzlan and Carpenter, 2006).

2. The energy ratio (ER) approach defines fatigue life ($N_1$) in the stress mode as the number of cycles at the point when the ER reaches its peak value in the relationship of ER vs number of cycles, while in the strain mode it is defined as the point when the ER slope diverges from a straight line in the same relationship (Rowe, 1993).

3. Pseudostrain energy – in this case, the fatigue index ($FI^R$) - is calculated based on the ratio of recovered pseudostrain energy to applied pseudostrain energy; fatigue life is defined using the average value of $FI^R$ within a 'plateau region'. Figure 2 shows a typical result for a fatigue test, evaluated using the TA, ER and $FI^R$ approaches for samples tested in strain and stress modes (for more details see (Ahmed and Khalid, 2015, Ahmed, 2016)).

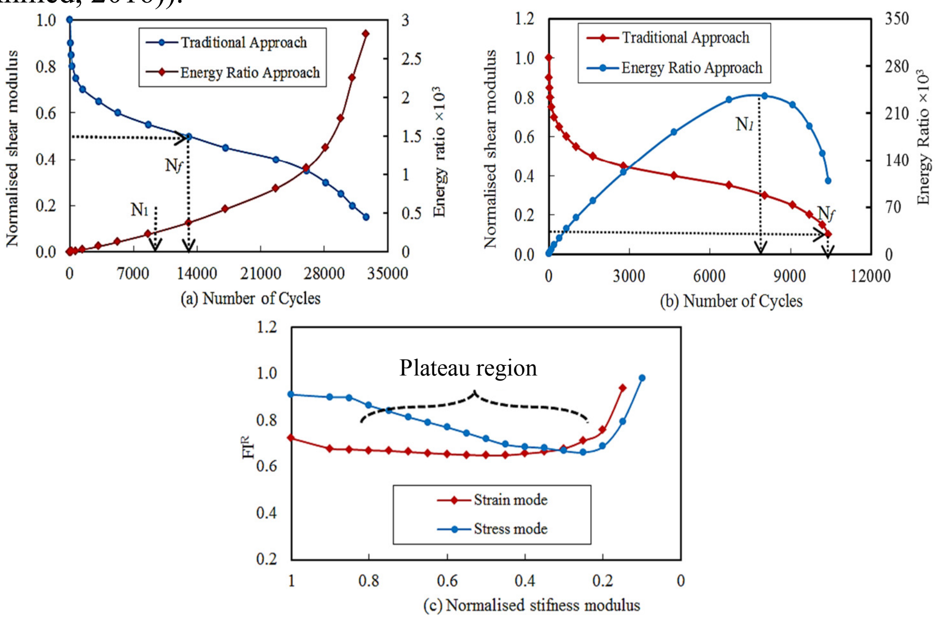


Figure 2: Fatigue performance analyses: (a) strain mode, (b) stress mode and (c) $FI^R$ approach (Ahmed and Khalid, 2015, Ahmed, 2016).

## 5. ANN Model based on fundamental parameters

The majority of the regression models that have been developed for predicting fatigue performance are based on two categories of variables: mechanistic variables (such as stress, strain and stiffness modulus) and volumetric properties such as air voids, void fields with asphalt or voids of binders (Monismith, 1969, Bonnaure *et al.*, 1980, Shook *et al.*, 1982, Monismith, 1985). Fatigue performance, in terms of number of cycles, was also evaluated using the parameters of the fatigue test outputs (stiffness modulus and phase angle as used in the traditional and energy ratio approaches (Tayebali *et al.*, 1992, Rowe, 1993, AASHTO, 2002, Kim *et al.*, 2003)).

Based on these works, all fundamental parameters were selected as inputs for the ANN models used in the current paper. These parameters are: the initial stiffness modulus ($G_o^*$), initial phase angle ($\delta_o$), shear strain amplitude ($\gamma$), shear stress amplitude ($\tau$), relaxation test coefficients ($G_1$, m), bulk density ($G_{bk}$) and air void percentage (AV%). The ANN model is therefore a function of these variables:

$$ANN_{model} \equiv f(G_o^*, \delta_o, \gamma, \tau, G_1, m, G_{bk}, AV\%) \quad (3)$$

The multi-layered general architecture shape presented in Figure 3.

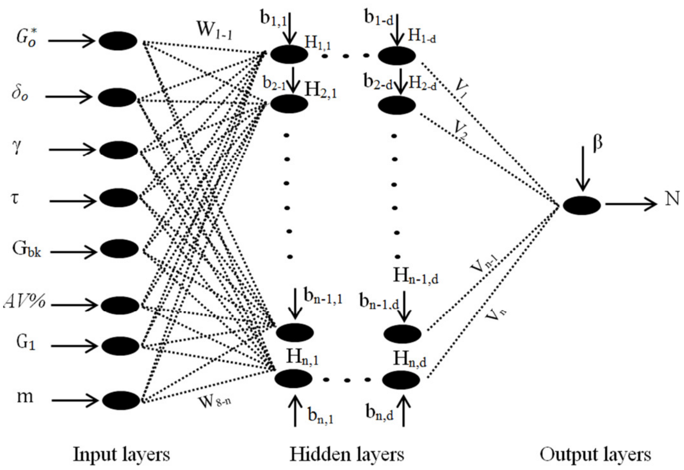


Figure 3: General architecture shapes for multi-layered ANN.

The total data for training and testing were collected from 46 DSR-samples tested in strain and 46 DSR-samples tested in stress test modes; the data were divided randomly into two different groups: 85% of the data for training and 15% for testing. The developed ANNs in the following sections have been classified according to fatigue performance approaches.

### *5.1: Traditional Approach ($N_f$)*

Multi-layered ANNs (as shown in Figure 3) were used to predict fatigue life. These included single and double hidden layers with 10, 15 and 20 neurons. The coefficient of determination ($R^2$) was employed to investigate the correlation between the actual and predicted fatigue life. The chosen architecture of the neural network was based on the highest $R^2$; it was found that the best ANN architecture for this purpose consisted of double hidden layers with 15 neurones in each layer. For simplicity, this multi-layered ANN is denoted as [$N_{Input}$-$15_{HiddenI}$-$15_{HiddenII}$-$\dot{N}_{Output}$], where N is the number of input parameters and $\dot{N}$ is the number of output parameters; this definition is used throughout this work. The input parameters for the controlled strain test mode ANN are: $G_o^*, \delta_o, \tau_o, G_1, m, AV\%$ $and$ $G_{bk}$, while in stress test mode the same input parameters are used except $\gamma_o$ replaces the stress amplitude $\tau_o$. This is because the strain amplitude in strain test mode is constant while in stress test mode the stress amplitude is constant. So the multi-layered ANN that was used in modelling the fatigue life ($N_f$) was denoted as [$7_{Input}$-$15_{HiddenI}$-$15_{HiddenII}$-$1_{Output}$] for both test modes. In this work, the MATLAB-2013a Neural Network Toolbox was used to create the ANN; the BP algorithm was used to train the neural network. For training, the Levenberg-Marquart algorithm was adopted because of its efficiency in training networks (Demuth, 2009). The relationships between the actual and predicted number of cycles by the ANNs are shown in Figure 4 for the strain and stress test modes.

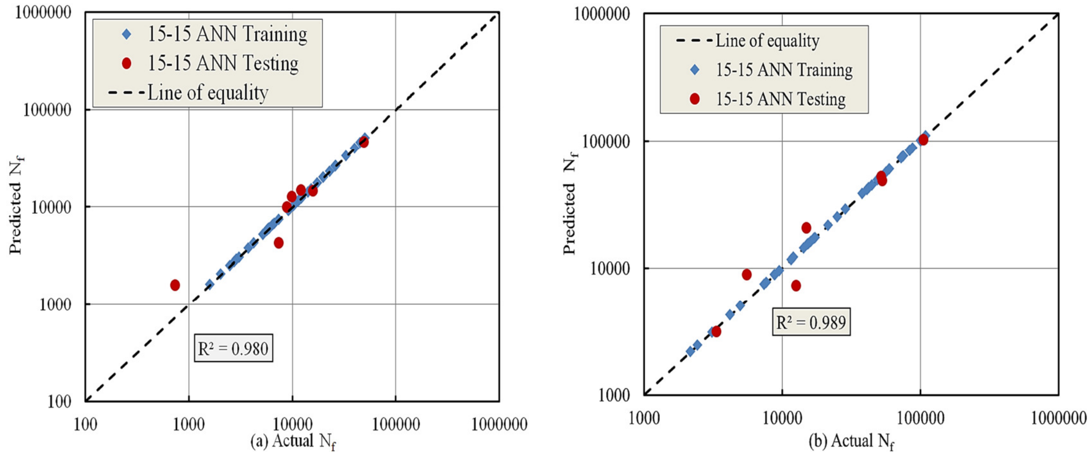


Figure 4: Actual against predicted number of cycles ($N_f$) of ANN model for: (a) strain mode, (b) stress mode.

The predictive performance of the trained neural networks is considered satisfactory and a high correlation, in terms of $R^2$, between actual and predicted values for the tested ANN is shown. The $R^2$ values show that there is no significant difference between both ANN models for stress and strain test modes. The correlation in both test modes are excellent (higher than 0.98), as shown in Figure 4.

### *5.2: Energy Ratio Approach ($N_1$)*

The same neural network architecture [$7_{Input}$-$15_{HiddenI}$-$15_{HiddenII}$-$1_{Output}$] as was used for the traditional approach ($N_f$) was chosen to model the number of cycles ($N_1$) for the energy ratio approach because it resulted in the highest $R^2$ value. The results revealed that there is high correlation between the actual and predicted number of cycles of the trained neural network, in both test modes, as presented in Figure 5.

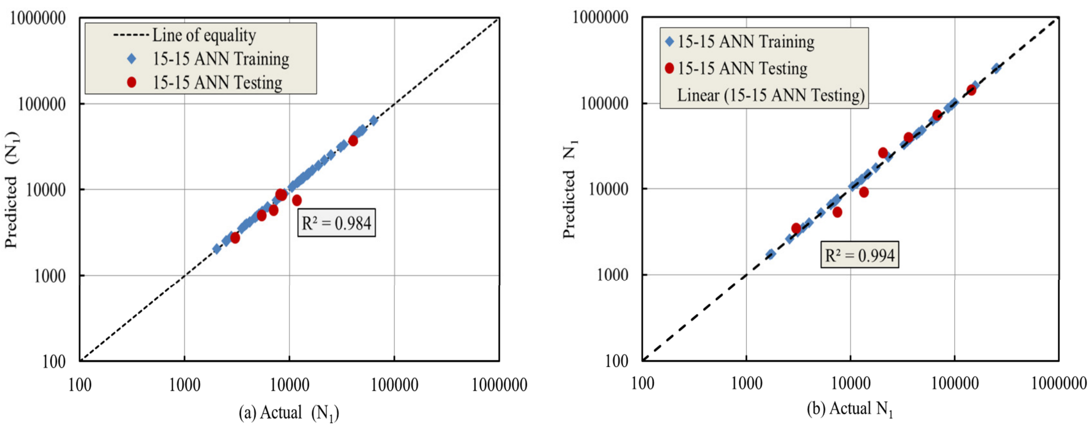


Figure 5: Actual against predicted number of cycles ($N_1$) of ANN model for: (a) strain mode, (b) stress mode.

Again, in the stress test mode the correlation was slightly higher than in the strain test mode, as was found with the traditional approach. This may be because the correlation between independent variables and number of cycles is better in the stress mode than the strain mode; however the correlation in both test modes are still excellent (higher than 0.98 for both modes, as shown in Figure 5).

### *5.3: Pseudostrain Energy ($FI^R$)*

The ANN [$7_{\text{Input}}$-$15_{\text{HiddenI}}$-$15_{\text{HiddenII}}$-$1_{\text{Output}}$], was also used for modelling $FI^R$ using the same input variables as described in the previous sections. The results revealed that there is an excellent correlation between the actual and predicted results; also there is no significant difference in $R^2$ between both modes (approximately 0.97 and 0.99 for strain and stress test modes respectively, as shown in Figure 6). The quality analysis of the all previous ANN models are presented in a section related to bias analysis at the end of this study (made to reflect the accuracy of the model's in predictions).

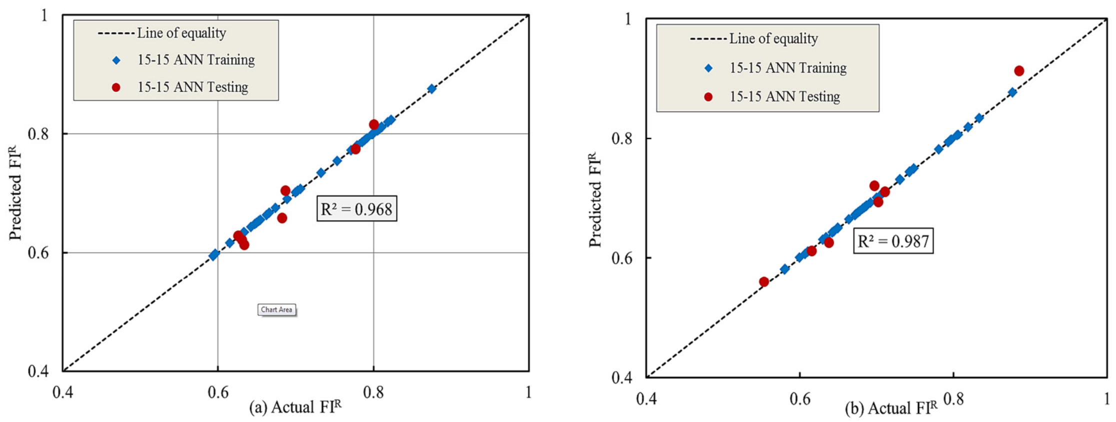


Figure 6: Actual against predicted $FI^R$ of ANN model: (a) strain mode, (b) stress mode.

## 6. ANN Model for independent fatigue mode test

In this section, a successful attempt was made to develop an ANN model which predicts fatigue performance, independent of test mode. The results of fatigue performance from two approaches were selected for modelling: the TA and $FI^R$ approaches. The ER approach was excluded because the definition of life as a number of cycles takes different criteria depending on the test mode, as the relation between energy ratio and number of cycles are different for both test modes as demonstrated in Figure 2. With the TA approach, the neural network was trained using the data of the fatigue life as a number of cycles at 50% and 15% of initial stiffness modulus irrespective of the test mode. The input parameters for the neural network were: $G_o^*, \delta_o, G_1, m, AV\%$ and $G_{bk}$. The shear stress amplitude, $\tau_o$, and shear strain amplitude, $\gamma_o$, have been excluded from the input parameters because the intention is to develop ANN model which works irrespective of the test mode. The resulting architecture is therefore [$6_{\text{Input}}$-$15_{\text{HiddenI}}$-$15_{\text{HiddenII}}$-$1_{\text{Output}}$]. The total data for training and testing were collected from 92 DSR-samples which were tested in strain and stress test modes; the data were divided randomly into two different groups: 85% of the data for training and 15% for testing.

### *6.1: Traditional Approach ($N_{f,50\%,15\%}$)*

The number of cycles in the TA was modelled using a neural network at 50% and 15% of the initial value of G*. Figure 7 shows the relationship between the predicted and actual $N_f$ at 50% and 15% of the initial G*. The predicting performance of the trained neural network is considered acceptable, as the $R^2$ values were 0.93 and 0.94 for 50% and 15% of initial G* respectively. This emphasises the feasibility of using the ANN model for predicting the fatigue performance as a function of the number of cycles, irrespective of test of modes.

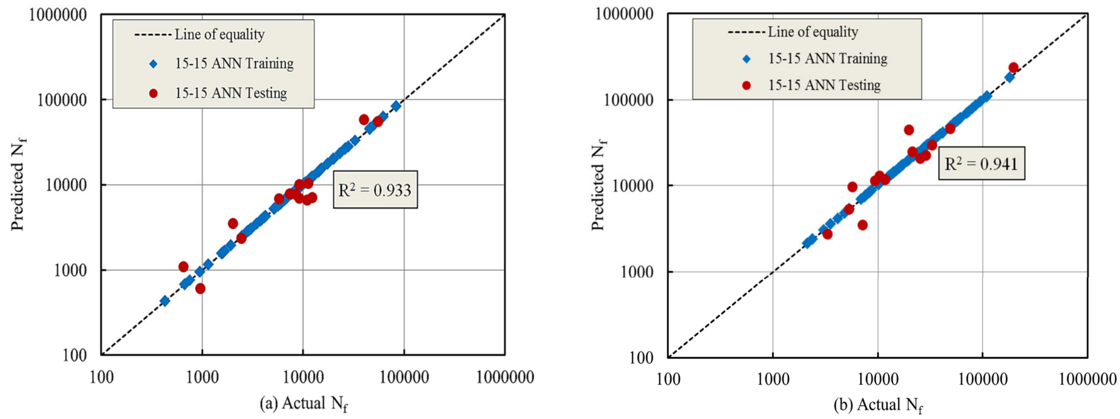


Figure 7: Actual against predicted number of cycles ($N_f$): (a) at 50% of initial stiffness modulus, (b) at 15% of initial stiffness modulus.

### *6.2: Pseudostrain Energy Approach ($FI^R$)*

Figure 8 shows results obtained using a neural network [$6_{\text{Input}}$-$15_{\text{HiddenI}}$-$15_{\text{HiddenII}}$-$1_{\text{Output}}$] for modelling the fatigue index ($FI^R$), independent of fatigue test modes. The correlation is excellent, as demonstrated from the high $R^2$ value (0.93) between the actual and predicted $FI^R$. This also emphasises the possibility of using ANN models to predict $FI^R$ irrespective of test of modes. To demonstrate the accuracy of these predictions, a bias analysis for these models is presented in the next section.

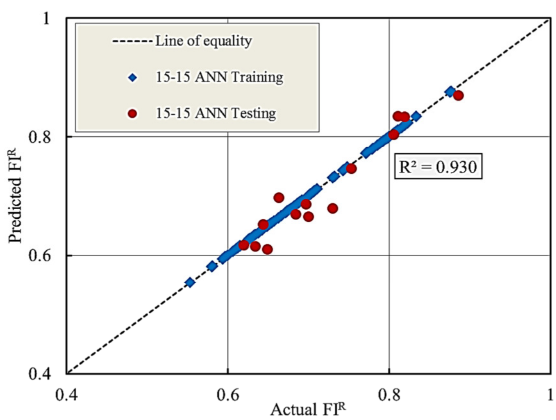


Figure 8: Actual against predicted $FI^R$ value of independent test modes.

## 7: The Bias Analysis of ANN Models

In the previous sections, $R^2$ was used to evaluate the accuracy of the ANN models for all the approaches; however overall 'goodness-of-fit' statistics such as $R^2$ do not necessarily tell the entire story regarding model accuracy. There may be overall biases in the predictions that can cause significant reduction in accuracy under certain conditions. Herein, the discussion was extended to study widely the bias of ANN models through the use of regression parameters. In this regard, three parameters were calculated based on the outcomes from the set of data that was used for the testing of each ANN. These parameters were: average error (AE) between predicted and actual results, evaluated using Equation (4) (Ceylan *et al.*, 2009):

$$AE = \frac{\sum_{i=1}^{N}(\varphi_p - \varphi_a)}{N} \tag{4}$$

(where: $\varphi_p$ and $\varphi_a$ are predicted and actual values for the set of tested data ), slope and intercept of the relationship between predicted and actual values. These three parameters will be compared with the optimum values that are presented by the line of equality (LQ). The LQ passes through the origin therefore the average error, intercept and slope are 0, 0 and 1, respectively. The model is close to the LQ when the slope and intercept approach 1 and 0, respectively. The discussion here comprised the bias analysis of the two categories of ANN models: ANN models based on fundamental parameters for the stress and strain mods and ANN models for independent test modes.

### *7.1: ANN models of Fundamental Parameters*

The ANN models in this case were developed based on the test of modes, i.e. strain and stress. The bias analyses were therefore divided into two categories: the stress and strain test modes. Figure 9 summarises the average error for the ANN models for all approaches, in both test modes. It can be noted that the ANN models under-predict in the strain mode for $FI^R$ and $N_1$ but over-predict in the stress test mode (as shown from the negative and positive average error values) while the behaviour was reversed when predicting $N_f$. Also, the ANN model prediction for stress has a lower tendency towards this bias than for the strain mode, if it was compared with the perfect value of the LQ, (as shown in Figure 9). Figure 10 shows the intercept values of the three approaches. For $FI^R$, the ANN model of the stress mode has the smallest prediction bias (Figure 10(a)). The intercept ranges for the $N_f$ and $N_1$ approaches are approximately 1100 to 100 cycles, as demonstrated in Figures 10(b) and 10(c) for both test modes. It is clear that the ANN model for the $N_1$ approach in the strain test mode is the closest to LQ because its intercept is slightly higher than 100 cycles; while for the stress mode it was higher than 750 cycles, as shown in Figure 10(c). In contrast, there is no significant difference in the $N_f$ approach for both test modes, where the intercept was approximately 1100 cycles. The third bias parameter is the slope, which is presented in Figure 11(where the smallest prediction bias ANN model is the closest to unity slope). The slopes of all ANN models are in a range between 1.1 and 0.9, which is acceptable. Overall, it is clear that the ANN models of the stress test mode have a lower prediction bias than the ANN models of the strain test mode.

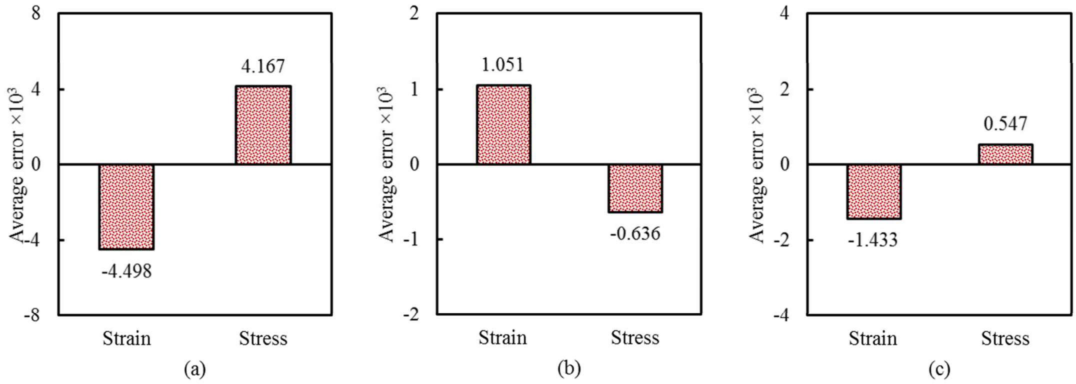


Figure 9: Average error of ANN models for different approaches in strain and stress test modes: (a) $FI^R$, (b) $N_f$ and (c) $N_1$.

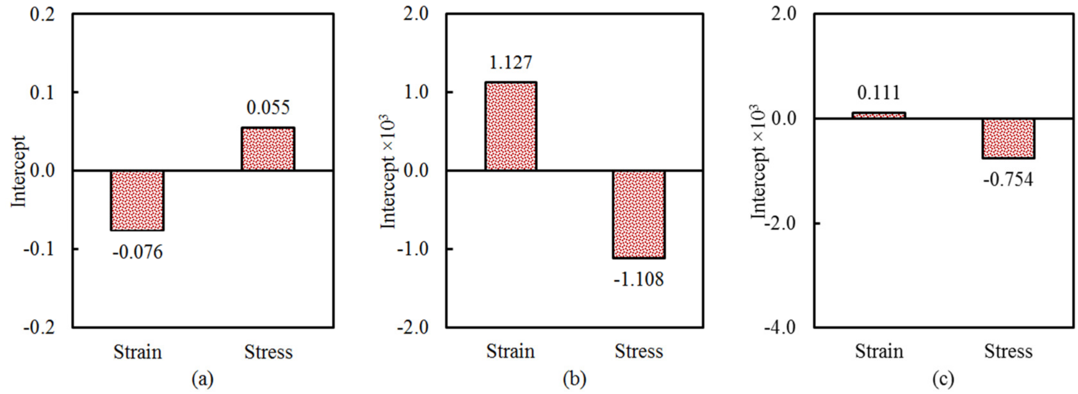


Figure 10: Intercept of ANN models for different approaches in strain and stress test modes: (a) $FI^R$, (b) $N_f$ and (c) $N_1$.

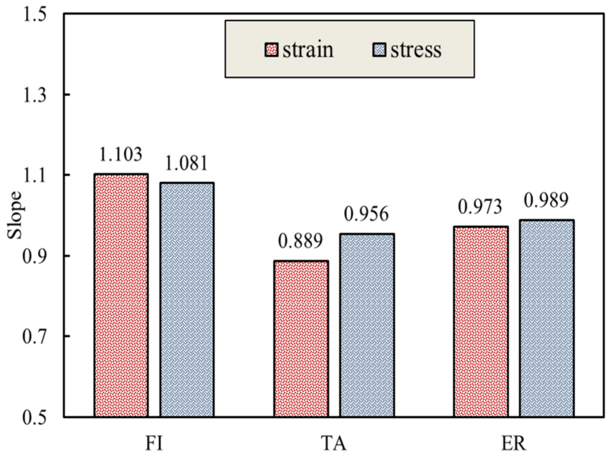


Figure 11: Slope of ANN models for different approaches in strain and stress test modes.

### *7.2: ANN models of Independent Test Modes*

Herein, ANN models were developed irrespective of the test of modes (i.e. strain and stress), for the $FI^R$ and $N_f$ approaches. Because the measurement unit of the $N_f$ approach is the number of cycles while $FI^R$ is without measurement unit, the bias analyses are presented in two categories: $N_f$ and $FI^R$ for average error and intercept whereas the slope analysis was conducted directly on $N_f$ and $FI^R$. Figure 12(a) shows the average error and intercept for the $N_f$ approach at 50% and 15% of the initial stiffness modulus. It can be seen that the ANN models for $N_f$ at 50% and 15% are over-predicting. Figure 12(b) displays the average error and intercept for the ANN model of $FI^R$. It is clear that the ANN model is under-predicting, although the average error is a very small value. Also, it can be seen that the intercept is a small value. The slope of the three ANN models is presented in Figure 12(c); it can be seen that the ANN models predicting $FI^R$ and $N_f$ at 50% have the same bias. In contrast, the ANN model predicting $N_f$ at 15% has the highest. Overall, it is clear that the ANN model of $N_f$ at 50% has the smallest prediction bias compared to the ANN models of $FI^R$ and $N_f$ at 15% models.

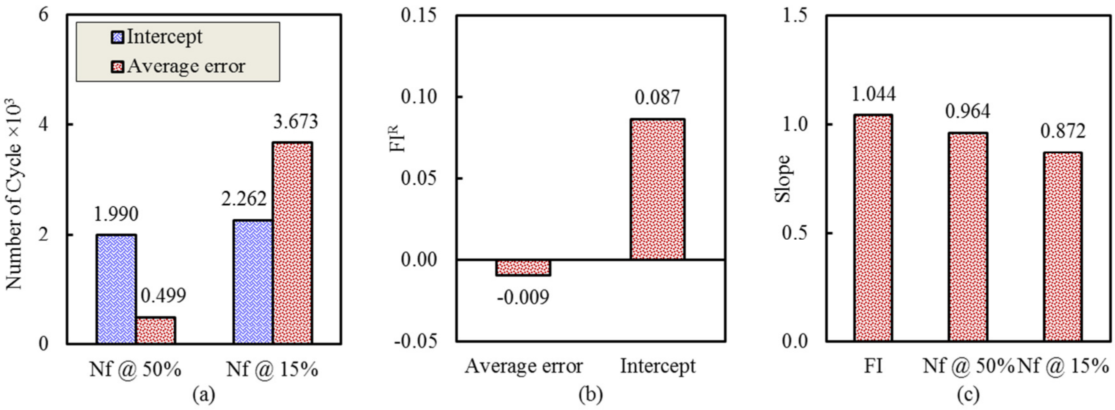


Figure 12: Bias parameters for ANN independent mode models.

## 8. Conclusions and Future Work

The practical advantage of this work is that it allows the fatigue life of HMA to be predicted without having to perform numerous fatigue tests, which are time consuming and expensive. The following outcomes were achieved based on the results and discussions:

1. The ANN approach, in this work, was used to create effective predictive models. While the ANN-based models were able to predict the fatigue life accurately (as evidenced by high $R^2$ values for the test data), these models are currently limited to the four types of HMA, tested at the specific strain and stress amplitudes described in the text.

2. Experimental data from fatigue tests of cylindrical samples, tested in the DSR, were used to train the neural networks. The neural networks were used to predict the fatigue performance of HMA in terms of the number of cycles ($N_f$ and $N_1$) and the fatigue index ($FI^R$). The ANN models used parameters from fatigue tests, i.e. initial stiffness modulus, initial phase angle, shear strain amplitude, shear stress amplitude and relaxation test coefficients in addition to volumetric properties, as input variables.

3. One of the objectives of this study was to develop ANN models based on the fatigue test modes, i.e. strain and stress, to predict fatigue performance. The results showed a high correlation between predicted and measured data for all approaches ($N_f$, $N_1$ and $FI^R$).

4. Another objective of the ANN approach was to develop models, independent of test mode, for predicting fatigue performance in terms of $N_f$ at 50% and 15% reduction of the initial stiffness modulus and $FI^R$. The same fatigue testing parameters were also used as input parameters for the neural networks. The results showed the capability of the ANN model to predict fatigue performance with high correlation, regardless of test mode.

5. Bias analysis for all ANN models was evaluated based on typical values of the line of equality. The analysis result showed that the ANN model for the stress mode has a lower prediction bias than the ANN models for the strain mode; while in the independent test mode models, the ANN model of $N_f$ at 50% gave smaller prediction bias when compared with the ANN models of $FI^R$ and $N_f$ at 15%.

6. While the ANNs performed well in this work, their performance was strongly influenced by the number of hidden layers and number of neurons used, i.e. the ANN architecture. In this case, the ANN architecture with two hidden layers and 15 neurons in each layer worked well based on the high determination coefficient ($R^2$) between the actual and predicted data

7. For future work the authors aim to retrain the ANN models using different test conditions, strain and stress amplitudes and different materials, to improve their predictive performance

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