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PREDICTING THE RHEOLOGICAL PROPERTIES OF BITUMEN-FILLER MASTIC USING ARTIFICIAL NEURAL NETWORK METHODS

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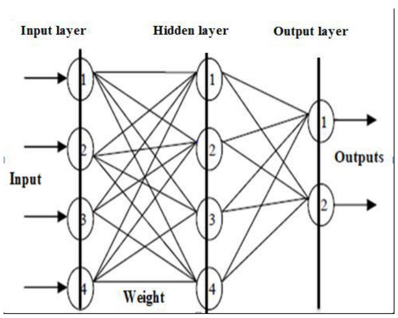
Graphical abstract



Abstract

This study was conducted to develop two types of artificial neural network (ANN) model to predict the rheological properties of bitumen-filler mastic in terms of the complex modulus and phase angle. Two types of ANN models were developed namely; (i) a multilayer feed-forward neural network model and (ii) a radial basis function network model. This study was also conducted to evaluate the accuracy of both types of models in predicting the rheological properties of bitumen-filler mastics by means of statistical parameters such as the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) for every developed model. A set of dynamic shear rheometer (DSR) test data was used on a range of the bitumen-filler mastics with three filler types (limestone, cement and grit stone) and two filler concentrations (35 and 65% by mass). Based on the analysis performed, it was found that both models were able to predict the complex modulus and phase angle of bitumen-filler mastics with the average R^2 value exceeding 0.98. A comparison between the two types of models showed that the radial basis function network model has a higher accuracy than multilayer feed-forward neural network model with a higher value of R^2 and lower value of MAE, MSE and RMSE. It can be concluded that the ANN model can be used as an alternative method to predict the rheological properties of bitumen-filler mastic.

Keywords: Artificial neural network, multilayer feed-forward neural network, radial basis function network, complex modulus (G*) and phase angle (δ)

Abstrak

Kajian ini dijalankan untuk membangunkan dua jenis peramalan model berdasarkan pendekatan rangkaian neuron tiruan (ANN) untuk meramalkan sifat-sifat reologi mastik-pengisi bitumen dari segi modulus dan sudut fasa yang kompleks. Dua jenis model ANN telah dibangunkan iaitu; (i) suatu model rangkaian neural galakan ke hadapan pelbagai lapisan dan (ii) model rangkaian fungsi asas jejarian. Kajian ini juga dijalankan untuk menilai ketepatan kedua-dua jenis model untuk meramalkan sifat-sifat reologi mastik pengisi bitumen melalui parameter statistik seperti pekali penentuan tertinggi (R2), min ralat mutlak terkecil (MAE), min ralat kuasa dua (MSE) dan punca min ralat kuasa dua (RMSE) untuk setiap model yang dibangunkan. Satu set dinamik reometer ricih (DSR) ujian data telah digunakan dalam penentuan mastic pengisi bitumen dengan tiga jenis pengisi (batu kapur, simen dan batu kersik) dan dua kepekatan pengisi (35 dan 65%). Berdasarkan analisis yang dijalankan, didapati bahawa kedua-dua model dapat meramalkan modulus dan sudut fasa mastik pengisi bitumen dengan nilai R^2 purata melebihi 0.98. Perbandingan antara kedua-dua jenis model menunjukkan bahawa asas fungsi model rangkaian jejarian mempunyai ketepatan yang lebih tinggi daripada model pelbagai lapisan rangkaian neural galakan ke hadapan dengan nilai yang lebih tinggi daripada R^2 dan nilai yang lebih rendah daripada MAE, MSE dan RMSE. Dapat disimpulkan bahawa model ANN boleh digunakan sebagai kaedah alternatif untuk meramalkan sifat-sifat reologi mastic pengisi bitumen.

Kata kunci: Rangkaian neural tiruan, rangkaian neural galakan ke hadapan, rangkaian fungsi asas jejari, modulus kompleks (G*) dan sudut fasa (δ)

1.0 INTRODUCTION

Therefore, an effective road design is required to ensure the people life to be more efficient. The road pavement must be designed for a long time with few maintenance requirements [1]. The stiffness of asphalt pavement is depending on the thickness of each layer of pavement design methods and the type of filler used. But the basic design of the pavement is dependent on the frequency of the pavement is exposed to the vehicle load, ground support conditions and weather conditions. The flexural stiffness of the pavement is also closely related to various aspects such as rutting, the modulus of resilience and fatigue. All these aspects can be seen through the rheological properties. Bitumen-filler mastic is a combination of bitumen and mineral fillers that highly influenced it rheological properties [2]. Bitumen is a thermoplastic material that binds the aggregate to be in stable and strong condition while the mineral filler material serves to fill the airspaces between aggregate and bitumen to improve the viscosity of the bitumen thus increase the pavement durability.

When the bitumen filler mastic are subjected to the burden of recurrent or persistent pressure, it will react in an elastic at low temperatures, viscous-elastic at moderate temperatures and viscous at high temperatures to which it is closely related to the stiffness. With the presence of filler mastic, the flexural stiffness of the bitumen will last longer because the main goal is to harden the bitumen in order to reduce the viscoelastic reaction of asphalt mixture or improving the elastic component and reduces the viscous component of bitumen.

Rheology refers to the study of the flow and deformation of materials under force applied routinely measured through the dynamic shear Rheometer (DSR) and dynamic mechanical analysis (DMA) tests. The DSR test (AASHTO T315-02) was used for measuring the viscoelastic properties of bituminous binders for a wide range of temperatures and frequencies (loading time) while the DMA is used to detect the rheological properties of the dynamics of bitumen through the test of the swing using the rheometer to understand the nature of viscous and elastic bitumen (various temperature and load rate) [3]. However, recognising that testing is generally laborious, time consuming and expensive, and requiring skilled operators [4]. Predictive models such an artificial neural network (ANN) model can be a valuable alternative tool for quantifying the rheological properties of bituminous binders including bitumen-filler mastics.

Artificial Neural Network (ANN) has been inspired by the feature found in the human brain. However, ANN structure is not as complex as the human brain neural network, but there are two similarities between biological neural networks and ANN. First, a block structure for both network is a simple counting devices (even neural network much simpler than the biological neural networks) and interconnected. Secondly, the connection between neurons will determine the function of the neural network [5]. ANN is a model which uses a combination of mathematical and simulation of biological neural system to process the information obtained to get the output in the form of predictions after the network was trained according to the data change pattern [6]. This system is able to recognize, capture and trace the pattern contained in the data set because of the high connectivity of neurons process information in parallel [7]. Therefore, at present, ANN approach be a valuable computational tool and is increasingly being used to solve complex problems as an alternative to more traditional techniques [8].

In the simplest form, ANN consists of single elements (neurons). Neurons or nerve will receive external signals and synthesize these signals into output signals. A simple conversion function is used in this process. Artificial neural networks also can be presented in a more complex form which contains a number of neurons that are connected to each other where the output signal from one neuron will be the input signal to one or more other neurons. The interaction that occurs between a large numbers of these neurons made ANN known as a model that can handle complicated and complex problem [9]. The basic structure for ANN is shown in Figure 1.

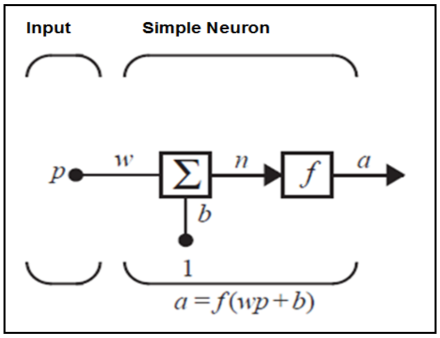


Figure 1 Basic structure of ANN

There are three different operations in a single input neuron network. The first input is scalar, *p* will be multiplied by the weight scalar, *w* to form a product , *wp* which is also a scalar. Both products, *wp* is added to the bias scalar, *b* to generate *a* net input, *n*. The function of the bias, *b* is equal to the weight, *w* but the value of bias is 1 and fixed. Finally, net input, *n* will be through the transfer function, *f* to produce a output scalar, *a*. The three processes are called 1) the weight function, 2) net input function, and 3) the transfer function [10].

Multilayer feed-forward neural network is the most widely used in prediction. It is train with a back-propagation learning algorithm, is a well-liked neural networks and it consists of neurons that are prearranged into layers as shown in the Figure 2. The first layer is a input layer, the last layer is the output layer, where n is the number of nodes of the output layer and the layers between are hidden layers [11]. It can contain more than one hidden layer but theoretical work has shown that one hidden layer is sufficient to estimate any complex nonlinear function [12].

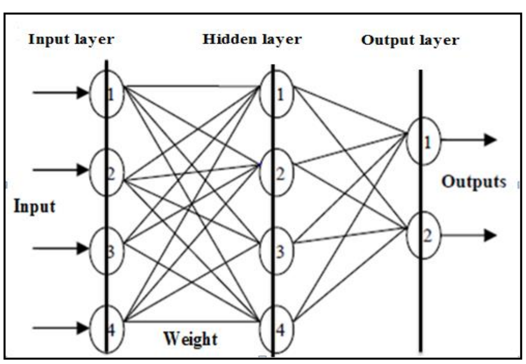


Figure 2 Multilayer feed-forward neural network structure

Generally, multilayer feed-forward neural network has multiple layers of input as *xj*, (*j* = 1,2, ... *n*) which represents the input signal source. Each input can be weighted before reaching the main body of the processing elements (neurons in the hidden layer) by the connection strength or weight, *wj*. Therefore, the signal that is transmitted via the connection strength is equal to a part of the original signal, *wjxj*. In addition, the input signal to the neuron must exceed the threshold value, *T* or bias, *b* to generate neuronal signals. After the impact of bias, *b* in the signals has been weighted, nonlinear function, *F* will enter to nonlinear units and then produces an output which is output can be input to other neurons [13].

The transfer function of the neural network is given by Equation 1 below:

$$Oi = Fi\left(\sum_{j=1}^{n}(w_{ij}x_{ij})\right) \quad (1)$$

provided the conditions of neurons are same as in Equation 2 below:

$$\sum_{i=1}^{n} w_{ij}x_{ij} \geq T_i \quad (2)$$

where subscript *i* and *j* represents a disputed neurons and input to the neuron respectively.

Radial basis function network is a type of feed-forward neural network composed of three layers, namely the input layer, the hidden layer and the output layer. Each of these layers has different tasks[14]. Figure 3 [15] show the radial basis function neural network Structure.

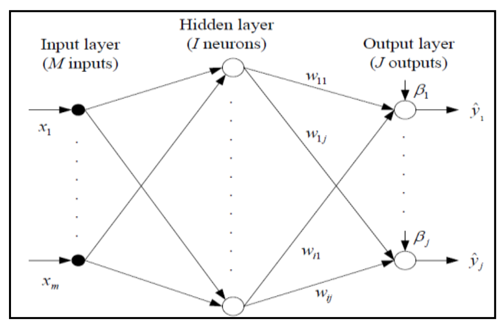


Figure 3 Radial basis function neural network structure

In the structure of the radial basis function network, data input, *X* is a vector of I-dimensions will be transferred to each hidden unit. The activation function of the hidden units is symmetrical in space for each input and output hidden units and is dependent on the radial distance between the input vector, *X* and the hidden unit. The output units for the hidden, hi which *i* = 1, 2, ..., *i* are as Equation 3 below:

$$hi\ (x) = \phi(\|x - ci\|) \quad (3)$$

where || || is Euclidean Norm, *ci* is central neurons in the hidden layer and ϕ( ) is the activation function where it is nonlinear function such as a gaussian kernel function, multiquadric, thinspline and exponential functions. Gaussian kernel function is a popular function used as transformer function in the hidden layer. The activation Gaussian kernel function are Expressed in equation 4:

$$\phi\ (x) = exp\left[-\ \frac{\| x-ci \|^2}{2p^2}\right] \tag{4}$$

Where x is the training data and ρ is the width of the Gaussian Kernel function. In radial basis function neural networks, the outputs of the input layer are determined by calculating the distance between the network inputs and hidden layer . The second layer is the linear hidden layer and outputs of this layer are weighted forms of the input layer outputs. Each neuron of the hidden layer has a parameter vector called center. The center and width of the kernel will join with each hidden unit in the network. Weight that connecting the hidden units and the output are estimated by the least min squares method. Finally, the reaction of each hidden unit is scaled by the weight of the connection to the output unit and it summed to generate a total output [16]. Therefore, k, the output of $\hat{y}k$ is such in equation 5 below:

$$\hat{y}_{k=} \sum_{i=1}^{I} w_{ij}\ \phi_i(x) +\ \beta_i \tag{5}$$

2.0 METHODOLOGY

This study is a contrived study using data measured from a laboratory experiment. The research framework of this study is shown in Figure 4.

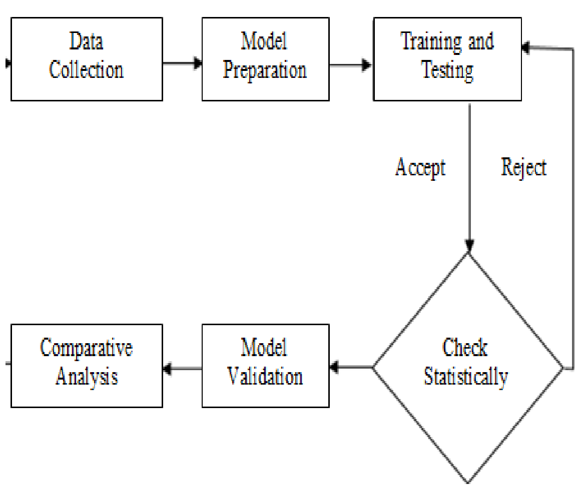


Figure 4 Research framework of this study

A set of dynamic shear rheometer (DSR) test data was used on a range of the bitumen-filler mastics with three filler types (limestone, cement and grit stone) and two filler concentrations (35 and 65% by mass). The amount of data used in this study is 1583 data. The data divided into three, namely 70% of the data used for model training process. A total of 15% would be used for model validation process and another 15% used for the testing process model. From 1583 data, a total of 1107 data used for the training process model, data 238 to be used for model validation process and 238 more data used for the testing process model. The division of the data is randomly according to the system used in MATLAB

The process involves in the ANN model preparation are the determination of the number of hidden layer in the models, the number of neuron in each hidden layer and the transfer function of the neural network multi-layer feed-forward and involves the determination of the spread value of radial basis function network. In MATLAB, each neural network has also been designed as a GUI (graphical user interface) with specific functions. This GUI that used in the preparation of model.

There are two neural network model used in the process of analyzing the data in this study name as neural network model multi-layer feed-forward and radial basis function network model. These models select data, create and train networks, and evaluate its performance using the mean squared error and regression analysis.

For multilayer feed-forward neural network model system has been designed in a toolbox. It can be used by typing '*nftool*' in the command window and the algorithm that used in this model is the Levenberg-Marquardt. Training on data can be repeated until the optimal results of the R^2 and MSE obtained. The structure is a model that has been designed as in Table 1.

Table 1 Structure of the network and the transfer function of ANN model

Subject	Transfer function
Input Layer	-
Hidden Layer	*Sigmoid*
Output Layer	*Linear*

Then, for radial basis function neural network has been designed to function '*newrb*' and will be called as shown in Equation 6.

net = *newrb (P, T, goal, spread, MN, DF)* (6)

where:

P = input vector matrix
T = target vector matrix
goal = mean squared error goal
spread = spread of radial basis function
MN = Maximum number of neurons
DF = number of neurons to display

The optimal dispersion will produce the best approximation of a function. However, many neurons are needed to meet the rapid change if the dispersion is too large. If dispersion is too small, many neurons are needed to cater the function well or it may not be able to produce a good network. Therefore, *newrb* function shall be called by different dispersion (spread) in order to find the best solution to a problem.

From 1583 data, 70% of the data involved in the training process as training set. Training set trained by using specific training algorithms until it achieve a minimum error. In the training process, the model try to learn the relationship between the input data and the output data and try minimized the difference between the target data and the predicted data. After that, further testing carried out to the other 15% of the data. This test based on the developed model in the training process. Training and testing process repeatedly done by changing the model parameters such as the number of neuron involve and the type of membership function used until the analysis produces an optimum output with the most minimum error. The division of data either it involve in training process or testing process is random.

Model validation process carried out after the optimum output from the training and testing is achieved. Validation is necessary to ensure the accuracy of the developed model. In this study, coefficient of determination, R^2 is used to evaluate the accuracy of the developed model. Meanwhile, the mean absolute error (*MAE*), mean squared error (*MSE*) and the root mean squared error (*RMSE*) is calculate to determine the most accurate model to predict the complex modulus, *G** and phase angle, *δ* of the bitumen filler mastic.

1. Coefficient of determination, R^2

$$\left(R^2 = 1 - \frac{\sum_{i=1}^{n}(x-y)^2}{\sum_{i=1}^{n}(x-z)^2}\right) \quad (7)$$

2. Mean absolute error, MAE

$$\left(MAE = \frac{1}{n}\sum_{i=1}^{n}|x-y|\right) \quad (8)$$

3. Mean squared error, MSE

$$\left(MSE = \frac{1}{n}\sum_{i=1}^{n}(x-y)^2\right) \quad (9)$$

4. Root mean squared error, RMSE

$$\left(RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x-y)^2}{n}}\right) \quad (10)$$

Where *x* is predicted value, *y* is actual value, *z* is average of actual value and n is number of data.

3.0 RESULTS AND DISCUSSION

Two models have been developed for multilayer feed-forward neural networks to prediction 1) the value of the complex modulus, *G**, and 2) the value of the phase angle *δ* of three different types of bitumen filled mastic in terms of the percentage of modifier and a control sample. Based on the results obtained from these models, the best network structure derived to predict the value of the complex modulus, *G** and phase angle, *δ* is 3-20-1 and 3-15-1. Table 2 describes the network structure and the transfer function used in this network.

Table 2 Structure of the network and the transfer function of multilayer feed-forward model

Item	Complex Modulus, G*		Phase Angle, δ	
	No. of Neuron	Transfer Function	No. of Neuron	Transfer Function
Input layer	3	-	3	-
Hidden layer	20	Log-sigmoid	15	Log-sigmoid
Output layer	1	Linear	1	Linear

Proportions graph are plotted to compare the results derived from developed model and experimental results in the laboratory.

Result for Multilayer Feed-Forward Neural Network

Figures 5 show the predicted values against actual values of complex modulus, *G** while Figure 6 shows the predicted values against actual values of phase angle, *δ* of bitumen filler mastic using multilayer feed-forward model. The point that scattered in the Figure 5 shows the proportion between predicted data and actual data, while a straight line present as a corresponding line that shows similarities between the actual data and predicted data. From Figure 5 and 6, the predicted value using this network model approached perfection where the value of coefficient of determination, R^2 for both is closer to 1.00 in the range of 0.98 to 1.00.

The mean absolute error (*MAE*) was used to calculate the average error between the actual data and predicted data. The *MAE* obtained from the calculation is 623 kPa for the modulus complex, *G** and 0.76° for the phase angle, *δ*. The small value of *MAE* shows that the structure of the network model has been designed with good form. Mean squared error (*MSE*) is similar with the square root of the mean error (*RMSE*).The *RMSE* obtained is 1778 kPa for the complex modulus, *E** and 1.26˚ to the phase angle *δ* the value of which is used to measure the accuracy of the model.

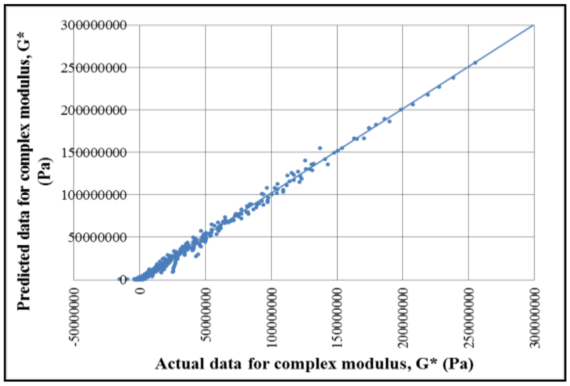


Figure 5 Graph of predicted value against actual value for complex modulus, G^* using multilayer feed-forward neural network model

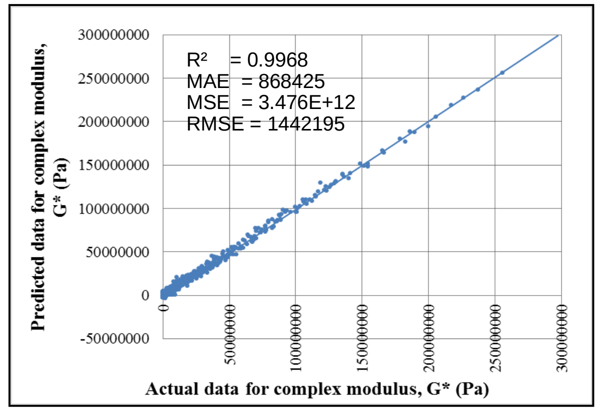


Figure 7 Graph of predicted value against actual value for complex modulus, G^* using radial basis function neural network model

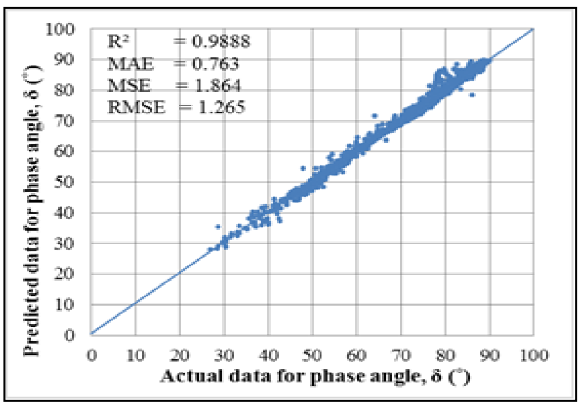


Figure 6 Graph of predicted value against actual value for of phase angle, δ using multilayer feed-forward neural network model

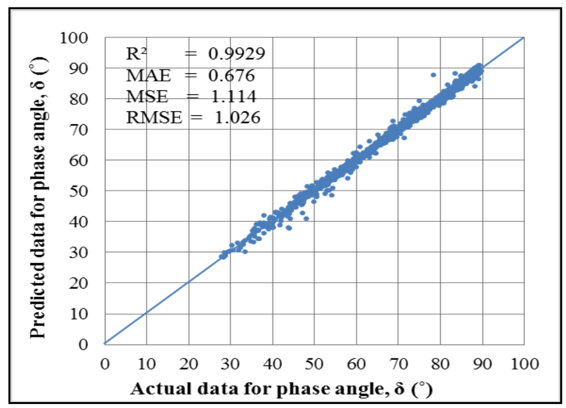


Figure 8 Graph of predicted value against actual value for of phase angle, δ using radial basis function neural network model

Result for Radial Basis Function Neural Network

The best results for models that have been developed were obtained from the determination of spread values through trial and error method. Figures 7 show the predicted values against actual values of complex modulus, G^* while Figure 8 shows the predicted values against actual values of phase angle, δ of bitumen filler mastic using radial basis function model. This model is also good in predict the value of the complex modulus, G^* and phase angle, δ as the value of R^2 obtained were approaching 1. The values are 0.9968 and 0.9929 respectively.

The average error between the predicted data and the actual data or MAE value is small which is 868 kPa for the modulus complex, G^* and 0.676° for the phase angle, δ while the *MSE* for the complex modulus, G^* and the phase angle, δ is 3.476E+12 Pa and 1.114°, respectively. The value will be squared to get *RMSE* of 14421 kPa of the complex modulus, G^* and 1.026° for the phase angle, δ. Figure 7 also shows that the majority of such data is on the line where it is shown that the predicted data is directly proportional to the actual data.

Statistical Analysis

Based on the analysis, it can be proved that the developed models are able to predict the complex modulus, G^* and phase angle, δ of bitumen filler mastic well. This is shown on Table 3, where the value of R^2 for both model is closer to 1.00 in the range of 0.98 to 1.00. This value indicates that both models have high accuracy in making the prediction.

Comparison between the two models the value of R^2 for radial basis function neural network model is higher than multilayer feed-forward neural network model as the value is almost approaching 1.00. Besides, the *MAE, MSE* and *RMSE* of radial basis function neural network model also lower than multilayer feed-forward neural network model. With this reasons, it can be concluded that radial basis function neural network model can predict the complex modulus, G^* and phase angle, δ better than the multilayer feed-forward neural network model because high R^2 value and a small *RMSE* values shows that the accuracy of the model is very high [18].

Table 3 Values for R^2, *MAE, MSE* and *RMSE*

	R^2	*MAE*	*MSE*	*RMSE*
Complex modulus, G*:				
Multilayer feed-forward neural network model.	0.9956	623856	4.893E+12	1778812
Radial basis function Neural network model	0.9968	86425	4.476E+12	1442195
Phase angle, δ:				
Multilayer feed-forward neural network model.	0.9888	0.763	1.864	1.265
Radial basis function Neural network model	0.9929	0.676	1.114	1.026

Comparisons have been made with studies performed by Hamim [16] on the study of rheological properties of asphalt mixture using artificial neural network. This study also uses two types of ANN model of neural network namely multi-layer feed-forward network and radial basis function to predict dynamic modulus, *E** and the phase angle, *δ* for asphalt pavement. Results from this study are shown in Table 5.

Table 4 The Coefficient of Determination Value, R^2

Item	R^2
Complex modulus, *E**	
Multi-Layer Feed-Forward Network	0.9947
Radial Basis Function Network	0.9953
Phase angle, *δ*	
Multi-Layer Feed-Forward Network	0.9977
Radial Basis Function Network	0.9997

From Table 4, it can be seen that the developed model in this study has a very high accuracy in predicting the value of the complex modulus, *G** as the average value of R^2 generated is very close to the value of 1.0 compared to the value of R^2 to the dynamic modulus, *E** generated in Table 5. However, in this study the average R^2 value obtained is low in predicting the value of the phase angle, *δ* compared with the values in Table 4, which is in the range of 0.9888-0.9929. This occurs because the experiments conducted by Hamım [16], complex modulus data that used is in the range of hundred while the complex modulus data developed in this study were within the range of millions. Furthermore, the number of neurons in the hidden layer of the phase angle used in the Hamım's study is 11, while the number of neurons in the hidden layer used in this study is 15. The range of data and no of neurons in the hidden layer are the factors that influence the accuracy of *ANN* model [19].

In addition, comparisons were also made on the *RMSE* value obtained from this study and studies that have been conducted by Xiao *et al*. [20]. It was found that *RMSE* obtained from previous studies in measuring the stiffness behavior of rubberized asphalt concrete mixture of cryogen at a temperature of 5 °C is 0.81 MPa, which is in the range of stiffness values between 0 to 30 MPa.

The *RMSE* value is 2.7% of the maximum range of the strength of the mixture. While in this study, the average *RMSE* values obtained for the complex modulus of both models is of 1.61 MPa in the range of stiffness values between 0 to 255.63 MPa and is 0.63% of the maximum range value of the stiffness. From the comparison that has been made, it was found *RMSE* for this study is lower compared to studies conducted by Xiao *et al*. [20] The lower *RMSE* value is preferable to developed a model.

4.0 CONCLUSION

In conclusion, it was found that the analysis process shows that radial basis function neural network model had a better accuracy in the prediction of the complex modulus, *G** and phase angle, *δ* compared to multilayer feed-forward neural network model. These studies also reinforces the evidence that the neural network model either radial basis function neural network model or multilayer feed-forward neural network model is able to predict the complex modulus, *G** and phase angle, *δ* for the bitumen filler mastic well and it can be inferred that the neural network models have an excellent potential to replace the existing analytical and empirical models in predicting the rheological properties of bitumen filler mastic.

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