Jurnal Kejuruteraan 35(4) 2023: 889-899
https://doi.org/10.17576/jkukm-2023-35(4)-11

Predicting the Rheological Properties of Bitumen-Filler Mastic Using Machine Learning Techniques

Abdalrhman Milad[a], Amirah Haziqah Mohamad Zaki[b], Hend Ali Omar[c], Shaban Ismael Albrka Ali[d], Naeem Aziz Memon[e] & Nur Izzi Md. Yusoff[b]

[a]Dept. of Civil Engineering, Faculty of Engineering & Built Environment, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia
[b]Dept. of Civil and Environmental Engineering, College of Engineering, University of Nizwa, P.O. Box 33, Nizwa PC 616, Ad-Dakhliyah, Oman
[c]Dept. of Civil Engineering, University of Tripoli, R6XF+46G, Tripoli, Libya
[d]Civil Engineering Department, Faculty of Civil and Environmental Engineering, Near East University, Near East Boulevard, 99138 Nicosia, North Cyprus
[e]Dept. of Civil Engineering, Mehran University of Engineering and Technology, Indus Hwy, Jamshoro, Sindh 76062, Pakistan

Corresponding author: a.milad@unizwa.edu.om

Received 15 August 2022, Received in revised form 12 January 2023
Accepted 12 February 2023, Available online 30 July 2023

ABSTRACT

This study uses the artificial neural network and response surface methodology to develop two models for predicting the rheological properties, complex modulus (G) and phase angle (δ) of bitumen-filler mastic. It also analyses and evaluates the accuracy of both models by determining the coefficient of determination (R^2), mean squared error (MSE), and root mean squared error (RMSE). The prediction models use the G* and δ data from a previous study by researchers at the Nottingham Transportation Engineering Centre to determine three types of bitumen-filler mastic (limestone, cement and grit stone) with varying filler concentrations of 15, 35, 40 and 65%. The analysis shows that both models perform well in predicting the rheological properties of bitumen-filler mastic. A comparison of the two models shows that the artificial neural network (ANN) has higher accuracy than the response surface methodology model, with an R^2 value exceeding 0.92. The results of the ANN achieve a higher R^2 value and lower MSE and RMSE values. In summary, the performance of the artificial neural network model is better than the response surface methodology model, which uses the full quadratic, pure quadratic, linear and interaction mathematical methods.*

Keywords: Artificial neural network, Response surface methodology, Complex modulus (G), Phase angle (δ)*

INTRODUCTION

The fillers added to asphalt pavement concrete are fine-dispersed powders produced by grinding rocks or industrial by-products (Rahaman et al. 2023). The structural capacity of a filler is associated with a highly developed pavement concrete surface (Lyapin et al. 2020). Therefore, effective road designs are essential to ensure the safety of road users. The road pavement design must ensure that the road pavement has a long service life with few maintenance requirements (Khamis et al. 2018). The natural properties of bitumen, such as weather resistance and the ability to support the heavy weight of traffic, make bitumen the primary and most frequently used material in the road construction industry. Additionally, the bitumen's viscous and elastic properties enhance pavement durability by acting as a binder that provides good adhesion for the aggregates (Vural et al. 2010) and serving as a waterproof layer and protective coating (Ghaffarpour & Khodaii 2009).

However, coatings stop weather damage by preventing the damaging effects of water penetration of flexible pavement. For example, pavement deterioration and cracking occur with excessive ageing that affects the durability of the bituminous paving materials. It also reduces the adhesion between the bitumen and the aggregates, resulting in the loss of material on the surface layer and weakening the asphalt mixture (Wu 2009). Researchers used fillers to overcome these problems since they can improve the adhesion properties between the mixture components (Rahim et al. 2021). Some researchers added mineral fillers to bitumen to form a bitumen-filler mastic with enhanced rheological properties (Russo et al. 2022). According to Lagos-Varas et al. (2020), fillers are beneficial for bitumen, depending on their physicochemical properties. Bitumen-filler mastic can ensure that the flexural stiffness of bitumen lasts longer (Khamis et al. 2018).

Rheology is the study of flow (Hunter et al. 2015). The rheological properties of bitumen are a basic indicator of its flow and deformation characteristics, and the rheological properties of bitumen binders are an indicator of the performance of flexible pavements at high or low temperatures (Adwan et al. 2021). Researchers used information on the rheological properties of bitumen binders to enhance fatigue resistance, permanent deformation and rutting (Bahia & Robert 1994). Given the crucial importance of rheological properties in bitumen performance, Zeghal (2008) introduced the ANN as an alternate to performing the test in the laboratory to cover the wide variety of factors that are known to influence the dynamic modulus. However, the testing with the DSR equipment is time-consuming, difficult, and expensive and must be carried out by skilled laboratory operators.

ANN is a subset of machine learning that is inspired by the human brain, imitating the way that biological neurons signal to one another (Abdolrasol et al. 2021). ANN is a computer model with an advanced biological neural network based on human brain activity (Hamim et al. 2020) the standard laboratory test procedures for establishing asphalt concrete |E*| and plotting the AC |E*| master curve are time consuming and require considerable resources. Therefore, this study aims to predict AC |E*| master curve by using data from a falling weight deflectometer (FWD. Abo-Hashema (2009) stated that ANN is useful for solving complex problems and overcome complexity, repetitive tasks, and time consumption, such processes should be implemented using a computer model (Adwan et al. 2022). ANN has a promising potential as a complementary or alternative analysis method for solving problems through parameter identification because it is an efficient, non-deterministic and highly realistic approximation method for many studies (Beltrán & Romo 2014), and it does not require mathematical equations to explain the experimental results. Instead, ANN solves problems by studying each element in the model (Zeghal 2008).

In civil engineering, ANN has been used to model material properties and behaviour and determine complex relationships between different properties because of its ability to learn and adapt (Araba et al. 2021; Shafabakhsh et al. 2015). For example, (Abo-Hashema (2009) used an ANN model to design the layers for flexible pavements, while Tasdemir (2009) used multi-layer perceptron, an ANN technique, to investigate the performance of modified asphalt mixtures at low temperatures. Ceylan et al. (2009) constructed an ANN model to predict the dynamic modulus (|E*|) of asphalt mixtures, and the results showed that the ANN model made more accurate predictions of |E*| than existing regression models. Zeghal (2008) has proven that the ANN technique could help engineers estimate the dynamic modulus of various asphalt mixtures with varying air void contents, grading and binders. These studies showed that ANN modelling were widely used in engineering applications (Desai et al. 2008).

Another method is the response surface methodology (RSM), the statistical techniques used to design experiments, develop models, evaluate the effects of factors and determine the optimal conditions (Desai et al. 2008). Hamzah et al. (2013) conducted an experimental test using this method and used the data to develop mathematical equations employing statistical techniques. They plotted the equations in statistical software with the shape of curves, contours or surfaces. This modelling approach is appropriate for establishing the relationship between parameters and multiple factors and generating the outputs for laboratory tests (Nassar et al. 2016).

The RSM model has also been applied in the engineering field. Khodaii et al. (2012) used RSM to evaluate the effects of grading and lime content on the by used the indirect tensile strength and tensile strength ratio of hot mix asphalt. Cha´vez-Valencia et al. (2007) used RSM to estimate the ageing resistance of bitumen binders in hot mixed asphalt, while Bala et al. (2018) used it to determine the optimum amount of Nona silica and bitumen to fabricate a modified nanocomposite asphalt mixture with high performance. Hamzah et al. (2013) optimised the binder content for asphalt mixtures using the RSM technique to evaluate the mixture's strength and volume characteristics. Xiao et al. (2022) developed a model for studying the influence of hot air heating parameters on the heating effect of asphalt pavements using RSM methods. The coefficient of 0.9884 achieved by the model confirmed its reliability.

Generally, ANN and RSM models are appropriate for predicting road pavement engineering (Milad et al. 2020). Therefore, this study developed ANN and RSM models to predict the rheological properties of bitumen-filler mastic and compared the results for both models to determine their effectiveness.

METHODOLOGY

This study used the data from laboratory experiments, and Figure 1 presents the research framework.

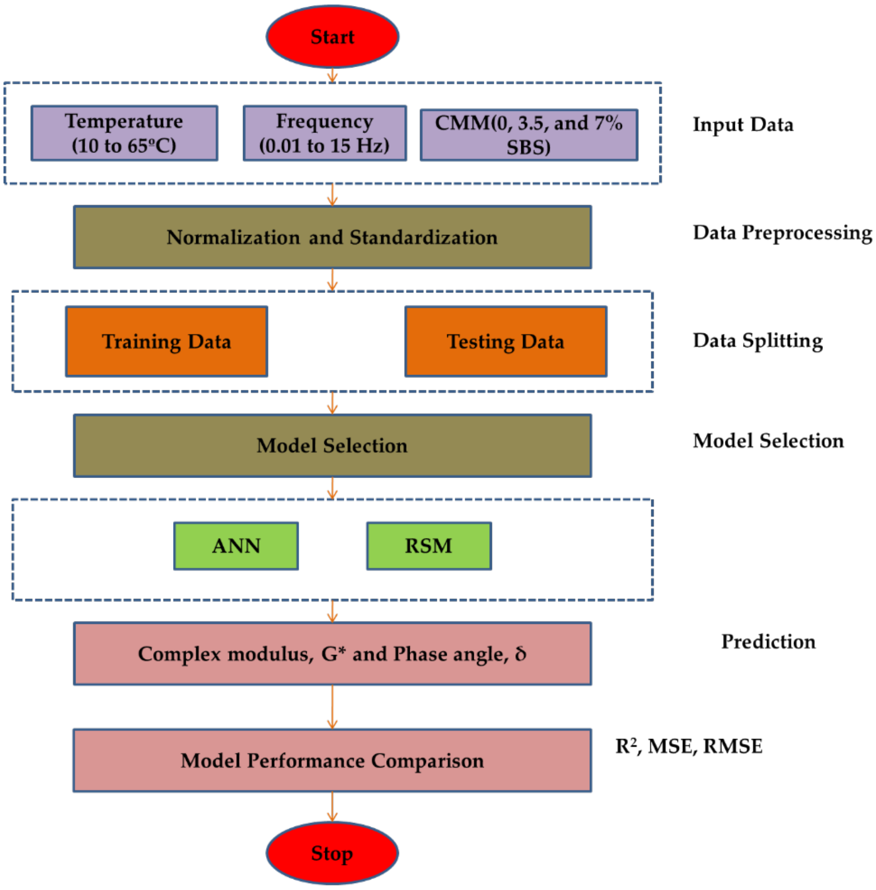


FIGURE 1. Research framework

DATA COLLECTION

The data for this study were from the studies carried out in the laboratory by skilled researchers. The data were from a dynamic shear rheometer (DSR) test on a bitumen-filler mastic data network with three fillers (limestone, cement and gravel). The test results served as target data for comparing the output from the ANN and RSM models. The input data in both models are temperature, frequency and modifier content.

The data were classified into different filler types and contents, bitumen-filler mastic by mass, bitumen-filler mastic by volume and ageing of bitumen-filler mastic. For the ANN model, 70% of the data was used to train the model, 15% for model testing and 15% for model validation.

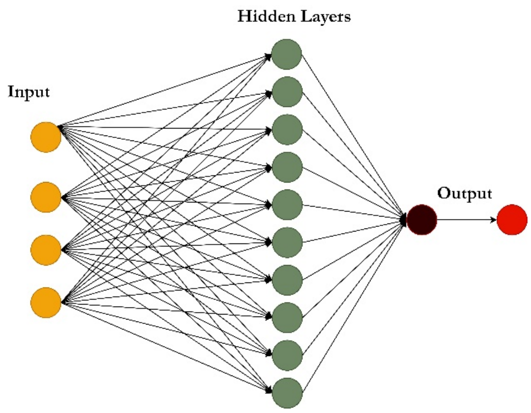


FIGURE 2. The framework for the ANN prediction model

DEVELOPING THE ANN MODEL

The ANN model development involved determining the number of hidden layers, the number of neurons in the hidden layers and the transfer function. Figure 2 presents an overview of the ANN model with the neuron layer processes hidden in the Matlab R2020a, with each neural network having a specific function. To use this model, type ‘nftool’ and upload the input and target data. The number of neurons is determined by trial and error to obtain optimal results closest to the target data.

DEVELOPING THE RSM MODEL

The RSM model is similar to the ANN model and designed using Matlab R2020a. The input and target data are in the form of a numeric matrix. To use this model, type ‘rstool’ and call the input and target data and the name of the mathematical equation. Figure 3 presents an overview of the RSM model.

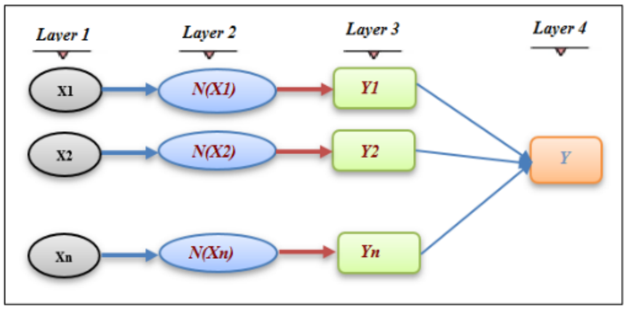


FIGURE 3. The framework for the RSM prediction model

TRAINING AND TESTING THE MODEL

After determining all required model parameters, the model underwent a training and testing process. The exercises for each model used a specific algorithm until each model achieved the minimum error goal of 0.00001.

About 70% of the data in the ANN model underwent the training process, while 15% was used for testing based on the model developed in the training process. The ANN model used the backpropagation Levenberg-Marquardt algorithm to reduce the error of the results.

The primary focus of the RSM model was training each dataset using statistical techniques. RSM is an intersection of the experimental design, the objective optimization and the statistical modelling. This model has four numerical system equations, pure quadratic, full quadratic, linear and interaction. Equations 1-4 give the expressions for numerical selections.

Pure quadratic:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1^2 + \beta_5 x_2^2 + \beta_6 x_3^2 + \varepsilon \quad (1)$$

Full quadratic:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \beta_7 x_1^2 + \beta_8 x_2^2 + \beta_9 x_3^2 + \varepsilon \quad (2)$$

Linear:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \quad (3)$$

Interaction:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \varepsilon \quad (4)$$

Where y_i is the predicted value, x_1 is input 1, x_2 is input 2, and x_3 is input 3. The variables y_i , x_1, x_2 and x_3 are the employed data, and variables β_0 to β_9 are the value generated by the RSM model.

VALIDATION OF THE MODELS

The models were validated after obtaining the optimum output from the training and testing process. The validation was necessary to ensure the accuracy of the developed models. This study used the coefficient of determination (R^2) to evaluate the accuracy of the ANN and RSM models. The mean squared error (MSE) and root mean squared error (RMSE) of bitumen-filler mastic were calculated to determine the most accurate model for predicting complex modulus (G*) and phase angle (δ).

1. Coefficient of determination, R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_0 + x_p)^2}{\sum_{i=1}^{n}(x_0 + x_p')^2} \quad (5)$$

2. Mean squared error, MSE

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_0 + x_p)^2 \quad (6)$$

3. Root mean squared error, RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_0 - x_p)^2}{n}} \quad (7)$$

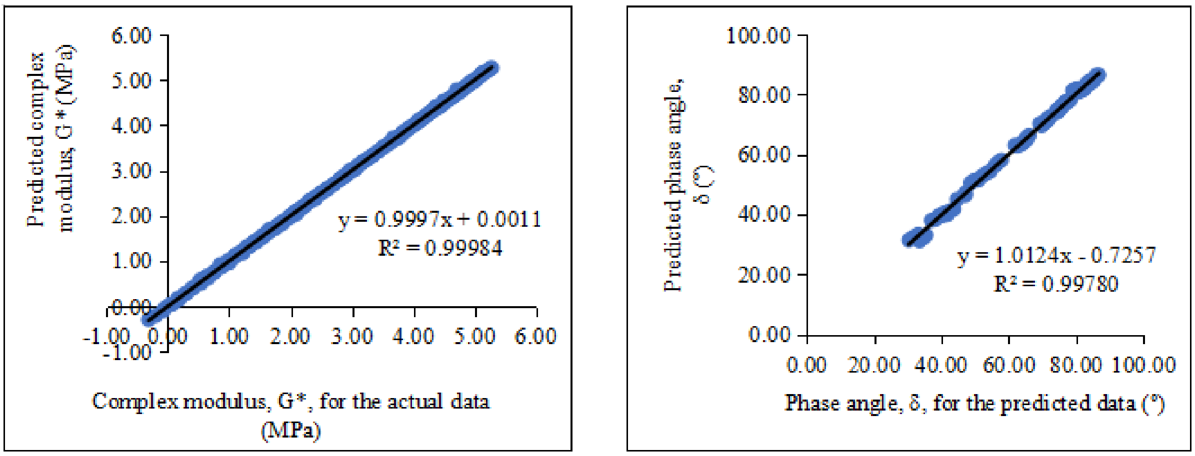
Where x_0 is the predicted value, x_p is the experimental value, x'_p is the average experimental value, and n is the number of data.

RESULTS AND DISCUSSION

This study used ANN and RSM to develop two models for predicting the G* and δ of fillers with varying percentages of modifiers and compared the G* and δ values predicted by the developed models with the experimental values by plotting proportions graphs and classifying the data into three bitumen-filler mastics. The points in the plot show the proportion between the predicted and experimental values that will achieve the output target. The straight line in the graph is the best predicted and experimental data.

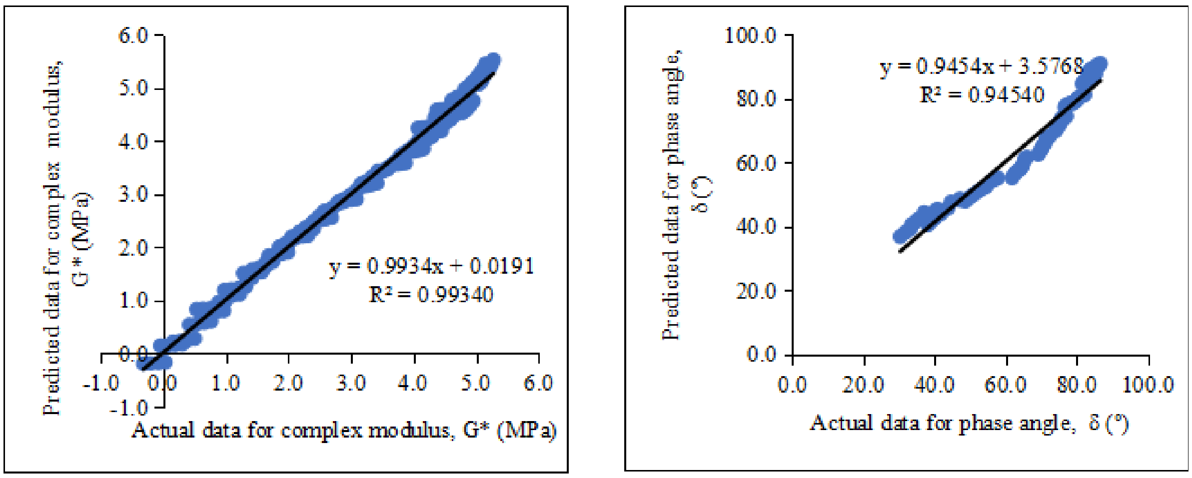
BITUMEN-FILLER MASTIC BY MASS

This study used a combination of grade 50 penetration bitumen with three different fillers. The selected fillers were crucial since each filler has specific physical and chemical properties capable of enhancing the bond between the aggregate and the bitumen mastic to achieve the optimum rheological properties at various operating temperatures. This study fabricated seven samples, E1, E2, E3, E4, E5, E6 and E7. Figures 4(a and b) are the graphs of the experimental G* and δ values of the bitumen filler mastic against the values predicted by the ANN model. Figures 5(a and b) are the graphs of the experimental G* and δ values of the bitumen filler mastic against the values predicted by the RSM model.



(a) (b)

FIGURE 4. Graphs for the experimental values against the values predicted by the ANN model for the bitumen-filler mastic by mass. (a) Complex modulus. (b) Phase angle.



(a) (b)

FIGURE 5. Graphs for the experimental values against the values predicted by the RSM model for the bitumen-filler mastic. (a) Complex modulus, G*. (b) Phase angle, δ.

This study predicted the rheological properties of bitumen-filler mastic by mass by comparing the ANN and RSM models. The RSM model can only be modelled using Equations 3 and 4 of the numerical method because it was based on Equations 1 and 2 and could not predict the data samples due to the significant difference between the maximum and minimum values of the output. The best result for the RSM was the model developed using Equation 4 for the perfect numerical model (interaction). Therefore, the interaction equation method was the best method for representing the overall results of the RSM model. Table 1 presents the R^2, MSE and RMSE values for the G* and δ for all data. Models E4 and E6 from the ANN modelling were the best models for predicting G* and δ of the bitumen-filler mastic by mass because of the high R^2 values for the G* and δ approached 1 (0.99988 and 0.99992) compared to the 0.99250 and 0.92960 values for RSM model. The RMSE values for G* and δ are the lowest (0.01934 MPa and 0.12550°) compared to the 0.14959 MPa and 3.71984° G* and δ values for the RSM model.

TABLE 1. The G* and δ predicted by the ANN and RSM model for the bitumen-filler mastic by mass

Sample	ANN			RSM		
	R^2	MSE	RMSE	R^2	MSE	RMSE
Complex modulus, G*						
E1	0.99982	0.00056	0.02363	0.99360	0.02006	0.14162
E2	0.99648	0.01259	0.11220	0.96450	0.11556	0.33994
E3	0.99950	0.00138	0.03714	0.99570	0.01237	0.11123
E4	0.99988	0.00037	0.01934	0.99250	0.02238	0.14959
E5	0.99942	0.00154	0.03929	0.99680	0.00892	0.09443
E6	0.99916	0.00256	0.05064	0.99340	0.02036	0.14267
E7	0.99984	0.00040	0.01996	0.99340	0.01690	0.12998
Phase angle, δ						
E1	0.99952	0.07852	0.28022	0.92450	13.04445	3.61171
E2	0.99938	0.10209	0.31951	0.91890	14.79875	3.84691
E3	0.99906	0.20584	0.45369	0.91940	19.38156	4.40245
E4	0.99942	0.11263	0.33560	0.91580	17.13717	4.13971
E5	0.99960	0.11957	0.34579	0.93690	20.94187	4.57623
E6	0.99992	0.01575	0.12550	0.92960	13.83724	3.71984
E7	0.99780	0.72038	0.84875	0.94540	17.65076	4.20128

BITUMEN-FILLER MASTIC BY VOLUME

The study investigated a combination of grade 50 penetration bitumen containing three types of fillers with the same filler content (40%). The selected filler concentration was crucial since it was based on the mechanical properties and workability of the asphalt mixture in the laboratory. The three data samples were E8, E9 and E10. Figure 6(a and b) are the graphs of the experimental G* and δ values of the bitumen filler mastic against those predicted by the ANN model. Figures 7(a and b) are the graphs of the experimental G* and δ values of the bitumen filler mastic against those predicted by the RSM model.

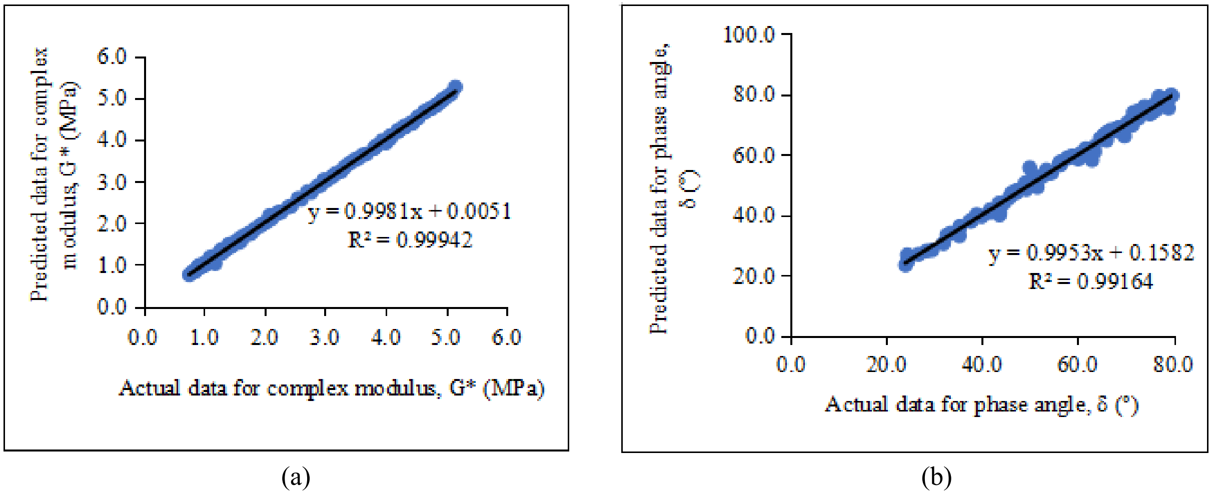
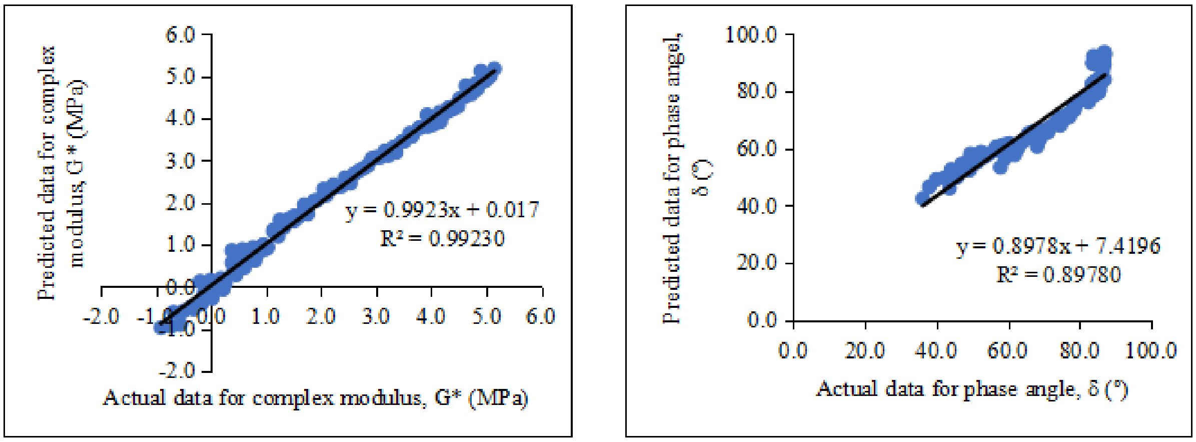


FIGURE 6. Graph for the experimental values against the values predicted by the ANN model for the bitumen-filler mastic. (a) Complex modulus. (b) Phase angle.



(a) (b)

FIGURE 7. Graph for the experimental values against the values predicted by the RSM model for the bitumen-filler mastic. (a) Complex modulus. (b) Phase angle.

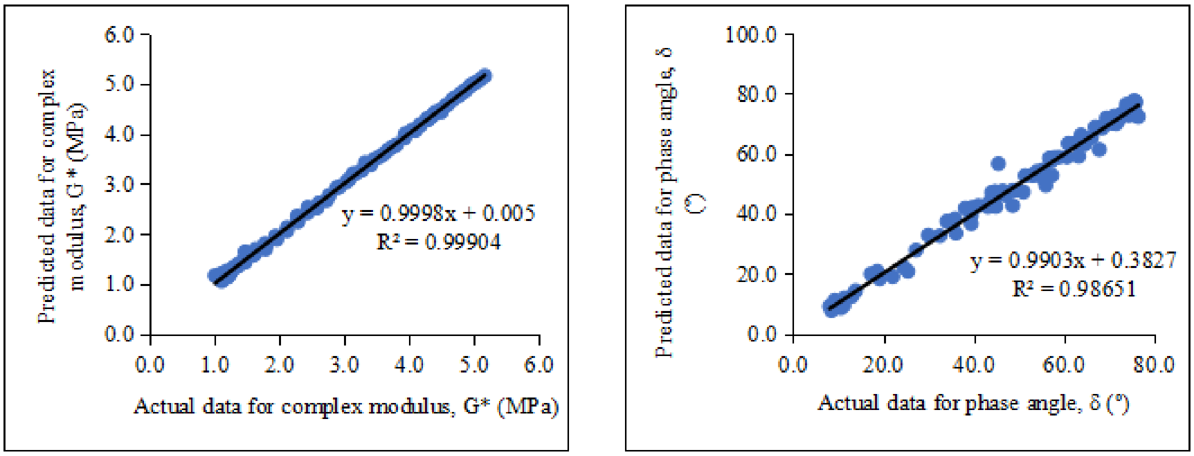
This study predicted the rheological properties of bitumen-filler mastic by volume by comparing the ANN and RSM models. The RSM model can only be modelled using Equations 3 and 4 because it was based on Equations 1 and 2 and could not predict the data samples due to the significant difference between the maximum and minimum output values. The best results for the RSM were obtained using Equation 4 for the perfect numerical model (interaction). Therefore, the interaction equation method was chosen as the best to represent the overall results of the RSM model. Table 2 presents the R^2, MSE and RMSE values for the output G* and δ for all data. Models E9 and E10 of the ANN modelling were the best models for predicting the G* and δ of the bitumen-filler mastic by volume. The 0.99978 and 0.99834 R2 values for the G* and δ approached one and were higher than the 0.99230 and 0.73350 G* and δ values for the RSM model. The 0.02532 MPa and 0.58600° RMSE values for G* and δ were the lowest compared to the 0.15758 MPa and 7.71090° for the RSM model.

TABLE 2. The G* and δ predicted by the ANN and RSM models for the bitumen-filler mastic by volume

Sample	ANN			RSM		
	R^2	MSE	RMSE	R^2	MSE	RMSE
Complex modulus, G*						
E8	0.99942	0.00116	0.03410	0.93190	0.14599	0.38209
E9	0.99978	0.00064	0.02532	0.99230	0.02483	0.15758
E10	0.99954	0.00134	0.03663	0.99060	0.02954	0.17186
Phase angle, δ						
E8	0.99164	2.13995	1.46286	0.35560	176.01527	13.26707
E9	0.99277	1.62506	1.27478	0.89780	23.13648	4.81004
E10	0.99834	0.34339	0.58600	0.73350	59.45797	7.71090

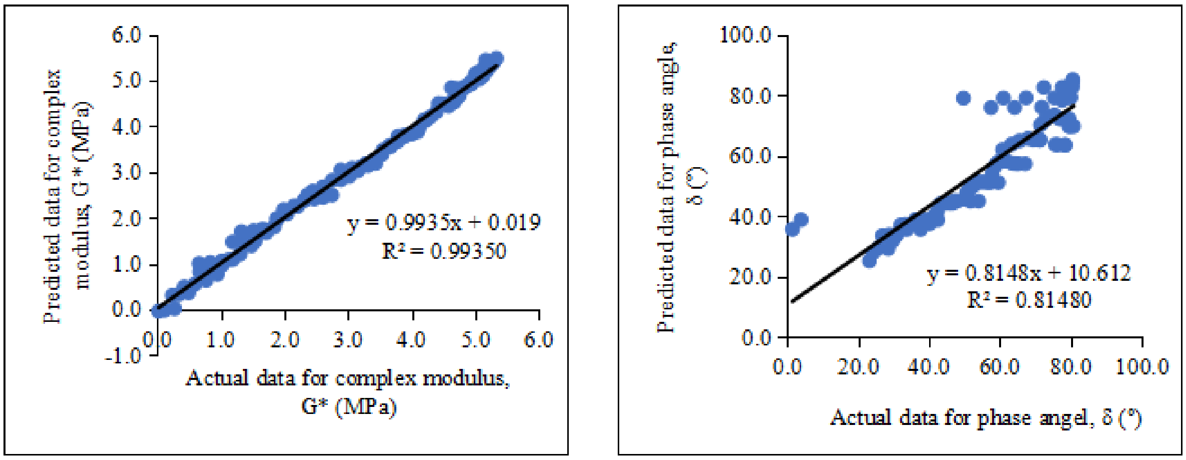
AGEING OF THE BITUMEN-FILLER MASTIC

Ageing occurs because the age hardening of the bitumen affects the durability of bitumen pavement materials. Pavement deterioration makes the asphalt more brittle, and this causes the bitumen-paved road surfaces and structures to fail. Considering the consequences of ageing, researchers have investigated incorporating additives into bitumen to prevent ageing. This study developed ten samples, F1, F2, F3, F4, F5, F6 F7, F8, F9 and F10. Figures 8(a and b) are the graphs of the experimental G* and δ values of the aged bitumen filler mastic against the values predicted by the ANN model. Figures 9(a and b) are the graphs of the experimental G* and δ of the aged bitumen filler mastic against the values predicted by the RSM model.



(a) (b)

FIGURE 8. Graph for the experimental values against those predicted by the ANN model for the aged bitumen-filler mastic. (a) Complex modulus. (b) Phase angle.



(a) (b)

FIGURE 9. Graph for the experimental values against those predicted by the ANN model for the aged bitumen-filler mastic. (a) Complex modulus. (b) Phase angle.

This study compared the performance of the ANN and RSM models in predicting the rheological properties of bitumen-filler mastic by mass. The RSM model can only be modelled using Equations 3 and 4 of the numerical method because it was based on Equations 1 and 2 and could not predict the data samples because of the considerable difference between the maximum and minimum output values. The RSM model developed using Equation 4 of the perfect numerical model (interaction) was the best model. Table 3 presents the R^2, MSE and RMSE values for the G* and δ for all data.

The F1 and F8 ANN models were the best models for predicting the G* and δ values of the aged bitumen-filler mastic because the 0.99988 and 0.99860 R^2 values for G* and δ approached one and were higher than the 0.99070 and 0.93620 for the RSM model. The 0.01842 MPa and 0.64781° RMSE values for G* and δ were the lowest compared to the 0.16669 MPa and 4.38522° for the RSM model.

TABLE 3. The G* and δ predicted by ANN and RSM for the aged bitumen-filler mastic

Sampel	ANN			RSM		
	R^2	MSE	RMSE	R^2	MSE	RMSE
Complex modulus, G*						
F1	0.99988	0.00034	0.01842	0.99070	0.02778	0.16669
F2	0.99904	0.00181	0.04256	0.94360	0.11374	0.33726
F3	0.99938	0.00130	0.03604	0.96620	0.07496	0.27380
F4	0.99980	0.00054	0.02318	0.99320	0.01824	0.13505
F5	0.99980	0.00050	0.02242	0.99350	0.01778	0.13333
F6	0.99954	0.00137	0.03702	0.99310	0.02263	0.15043
F7	0.99962	0.00114	0.03380	0.99380	0.01942	0.13935
F8	0.99966	0.00107	0.03269	0.99330	0.02063	0.14364
F9	0.99986	0.00037	0.01915	0.99490	0.01477	0.12153
F10	0.99958	0.00077	0.02773	0.99280	0.01427	0.11945
Phase angle, δ						
F1	0.99696	0.57263	0.75673	0.75220	49.90932	7.06465
F2	0.98651	5.85719	2.42016	0.33450	310.05968	17.60851
F3	0.96597	11.13046	3.33623	0.37000	221.52391	14.88368
F4	0.98666	3.00343	1.73304	0.70790	67.86228	8.23786
F5	0.92989	25.40609	5.04045	0.81480	72.09817	8.49106
F6	0.99698	0.67327	0.82053	0.92440	18.19811	4.26592
F7	0.99263	1.85585	1.36229	0.92560	18.54203	4.30605
F8	0.99860	0.41966	0.64781	0.93620	19.23014	4.38522
F9	0.99263	2.02855	1.42427	0.94070	17.52647	4.18646
F10	0.93227	10.21448	3.19601	0.75260	39.61992	6.29444

COMPARING THE ANN AND RSM MODEL

The R^2, MSE, and RMSE values predicted by ANN and RSM for each data showed that both models could predict the rheological properties of bitumen-filler mastic. In both types of material additive to the predicted value of the complex modulus, G*, and phase angle, the ANN model outperforms the RSM model.

The R^2 for the ANN model ranged between 0.92 to 1.00 and was higher than the RSM model. The MSE and RMSE values for the ANN model were lower than for the RSM model, indicating that the ANN model made better predictions than the RSM model with higher accuracy and less error.

The results of this study are similar to those of Milad *et al*. (2020), who used neural networks and response surface methodologies to investigate flexible pavement maintenance treatment. They found that the ANN and RSM model produced quick and good predictions, but the neural networks made more accurate predictions than the statistical and RSM methods based on mathematical models. Table 4 presents the results of this study.

TABLE 4. The R^2, MSE and RMSE for the ANN and RSM prediction models.

Prediction Model	R^2	MSE	RMSE
ANN	0.99	0.00137	0.037
RSM (Full Quadratic)	0.93	0.00230	0.048

The high R^2 and low RMSE values of the ANN and RSM models showed that the models made accurate predictions of the rheological properties of bitumen-filler mastic. The ANN and the RSM model based on the full quadratic mathematical method predicted the treatment techniques accurately, although the predictions by the ANN model were more accurate because it was adaptable and thus able to add a new G* and δ.

This study has proven that the ANN and RSM model are alternative prediction tools for predicting the G* and δ of the rheological properties of bitumen-filler mastic.

CONCLUSION

The ANN and RSM models developed for predicting complex modulus and phase angles value have a high prediction accuracy. A comparison of both models revealed that the ANN model made more accurate predictions of the rheological properties of bitumen-filler mastic than the RSM model. The R^2 for the ANN model was higher than the RSM model and approached 1.00, and the MSE and RMSE values of the ANN model were slightly less than the RSM model.

ACKNOWLEGMENT

The authors would like to thank Universiti Kebangsaan Malaysia for supporting this research (GUP-2021-025).

DECLARATION OF COMPETING INTEREST

None

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