

## Research Article

# Evaluating the Performance of Aluminum Oxide Nanoparticle-Modified Asphalt Binder and Modelling the Viscoelastic Properties by Using Artificial Neural Networks and Support Vector Machines

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The effect of aluminum oxide nanoparticles ( $\text{Al}_2\text{O}_3$ ) on the 60/70 penetration of asphalt cement (AC) was investigated in terms of the physical and rheological characteristics by using the Superpave testing procedures.  $\text{Al}_2\text{O}_3$  at 3, 5, and 7% concentrations were blended with 60/70 penetration of grade AC. Conventional testing procedures were adopted regarding the physical characteristics, while dynamic shear rheometer (DSR) testing procedures were conducted to evaluate the high and low temperature failure parameters. In addition, heuristic modelling techniques, artificial neural networks (ANN), and support vector machines (SVM) were employed to predict the performance characteristics of AC by using the mechanical testing conditions. The frequency sweep test and multiple stress creep recovery (MSCR) test results revealed that the optimum composition of  $\text{Al}_2\text{O}_3$  was at 5% concentration considering the high temperature performance characteristics since further addition of the  $\text{Al}_2\text{O}_3$  resulted in degradation in the enhanced properties due to agglomeration of the nanoparticles in the blend. On the contrary,  $\text{Al}_2\text{O}_3$  5% demonstrated the lowest viscoelastic behavior at intermediate temperatures. The higher complex modulus ( $G^*$ ) and lower phase angle ( $\delta$ ) parameters indicated that the increase in stiffness due to the modification process was at the cost of losing elastic properties against fatigue cracking. Moreover, based on the statistical performance indicator, coefficient of determination ( $R^2$ ), it was observed that the ANN models for predicting  $G^*$  and  $\delta$  achieved a prediction accuracy of 0.989 and 0.911 while SVM models were able to achieve 0.984 and 0.929, respectively, considering the training datasets. On the other hand, it was noted that SVM models outperformed the ANN models in terms of a smaller gap between the results obtained from the training and testing datasets. The difference between the training and testing datasets for  $G^*$  and  $\delta$  parameters for the SVM models were 3.2% and 6.8% while for the ANN models, the differences were 11.6% and 9.5%, respectively, indicating that the ANN models were more prone to the overfitting phenomenon.

## 1. Introduction

Bituminous materials are found as natural deposits or obtained as a product from the process of the distillation of crude oil. The quality of bitumen relies on its adhesive properties and depends on the source it is obtained [1]. Bitumen is a viscoelastic material, meaning that it softens when subjected to heat and hardens when cooled. They are categorized by their dependability or capability to flow at wide ranges of temperatures [2]. Due to the limitation of bitumen regarding the temperatures, adding additives to base bitumen is one of the best techniques to enhance the properties of bitumen. Many materials were used as modifiers of bitumen, namely, polymers, plastic, steel slag, and glass. It was indicated that the usage of polymers to modify bitumen was able to improve the quality and mitigate the distresses on the mixture which leads to an increase in the durability [3–5]. On the other hand, the incompatibility between the bitumen and polymers leads to phase separation among the blends which reduces the strength of the pavement [6, 7].

As a result, nanomaterials have been introduced as another way to enhance the bitumen properties and to improve compatibility between the bitumen and the polymers. Nanomaterials have been developed and incorporated rapidly in the design of flexible pavement roads as it has unique properties. These properties include high surface work, a large fraction of surface atoms, structural features, quantum effects, and spatial confinement [8]. It was predictable that modification of bitumen with nanomaterials would improve the properties of bitumen including an increase in stiffness, less temperature susceptibility, and improved strength against weather-induced and moisture damage. Some nanomaterials that have been used to modify polymer-modified bitumen includes nanoclay, nanofibers, carbon nanotubes, and nanosilica. In the previous studies conducted by using the aforementioned nanomaterials, it has been reported that the performance of bitumen-modified with nanomaterials showed significant improvement in the complex modulus while the phase angle was reduced, indicating that the rutting parameter of modified bitumen could be minimized this way [9–11].

On the other hand, although nanomaterials are promising, some of them are expensive and demand further research for exploration and optimization for bitumen modification purposes prior to field testing and applications [9]. In addition, laboratory testing of materials is time- and resource-intensive. In this vein, advanced statistical modeling and soft computing modeling approaches are in vogue in the prediction of the performance characteristics of asphalt binders [12].

Artificial neural networks (ANN) is a nonlinear, non-parametric modelling technique that is among the soft computing methods which have proved to offer a high degree of accuracy in computational prediction of the results observed in laboratory testing [13]. A significant amount of research has been dedicated to modeling of asphalt mixtures with the ANN, however, investigations on binder performance were mostly limited to be addressed by the experimental procedures. Lui et al. [14] studied the ANN and Iowa

models to predict dynamic modulus of base and recycled shingle asphalt mixtures. El-Badawy et al. [15] compared regression models and ANN models with Witczak and Hirsch predictive models for forecasting dynamic modulus of asphalt mixture. Tapkın et al. [16] presented a study to predict the strain accumulation in polypropylene (PP)-modified marshal samples. Abedali [17] conducted a comparison study among the performance of multiple linear regression models (MLR) and ANN with base asphalt binder. Ziari et al. [18] performed a similar study to Abedali with carbon nanotube (CNT)-modified asphalt binders to predict the rutting performance. Venudharan and Biligiri [13] employed the ANN to predict the rutting performance of asphalt binders with different crumb rubber (CR) gradations.

Support vector machines is another subfield of artificial intelligence methods which focuses on the development of data modelling algorithms which can learn from trained data points. Recently, SVM is gaining the attention of researchers towards developing classification and regression models due to its performance and attractive features such as embodying the structural risk minimization (SRM) principle which is known to perform better than the empirical risk minimization (ERM) principle employed by the neural networks [19]. Previously, Maalouf et al. [20] studied the potential use of SVM to predict resilient modulus of asphalt mixes and compared their model performance with the traditional least squares (LS) method. Gopalakrishnan and Kim [19] utilized the support vector machine approach to predict the stiffness for the hot mix asphalt. Zhang et al. [21] conducted a research study to predict Marshall parameters of flexible pavement design by using SVM and genetic programming (GP). Another study conducted by Uwanuakwa et al. [22] utilized Gaussian process regression (GPR), recurrent neural networks (RNN), ANN, and SVM to predict the rutting and fatigue parameters in modified asphalt binders.

The objective of the current study was to conduct experimental procedures to assess the rheological and physical characteristics of base and nanoalumina-modified binders and to utilize artificial intelligence models by considering the rheological behavior of the asphalt binders under different mechanical test conditions in order to forecast the experimental outcomes at a more extensive range of testing conditions which the asphalt is expected to undergo during its lifetime.

## 2. Methods and Data Analysis

*2.1. Sample Preparation of Modified Asphalt Binders.* The base asphalt cement (BAC) used in the current study was 60/70 penetration of grade and it was provided by Petronas Petroleum while the additives ASA and  $Al_2O_3$  were purchased from the Shijiazhuang Chanchiang Corporation Company in China. Physical properties regarding the material properties are listed in Table 1.

The blending of aluminum oxide nanoparticles ( $Al_2O_3$ ) into BAC was performed by adding different concentrations: 3%, 5%, and 7% by the weight of base asphalt. The asphalt was heated to a desirable temperature ( $150^\circ C$ ) then the nanoparticles were incorporated into the blend gradually,

TABLE 1: Physical properties of the base AC, ASA, and Al<sub>2</sub>O<sub>3</sub>.

Materials	Parameters	Units	Test methods	Values
BAC (60/70)	Specific gravity	—	ASTM D70	1.03
	Penetration at 25°C	dmm	ASTM D5	70.0
	Softening point	°C	ASTM D36	46.0
	Viscosity at 135°C	Pa·s	ASTM D4402	0.50
ASA	Specific gravity	—	—	0.30
	Size	mm	—	2.00
Al <sub>2</sub> O <sub>3</sub>	Size	nm	—	13.0

and the whole samples were mixed under the temperature of 170°C by using a high shear mixer at a speed of 5000 rpm for 90 minutes.

**2.2. Physical Properties.** Assessments of physical characteristics of base and modified asphalt binders were performed by following the American Society for Testing and Materials (ASTM) criteria. The penetration test was performed according to ASTM D5 and softening point test was implemented according to ASTM D36, while the viscosity test was performed according to ASTM D4402.

**2.3. Viscoelastic Properties of Modified Asphalt Binders.** A dynamic shear rheometer (DSR) was used to conduct frequency sweep test to evaluate the changes of viscoelastic properties, stiffness ( $G^*$ ), and phase angle ( $\delta$ ) for base and modified asphalt binders. The tests were conducted under various temperatures (10, 15<sup>+10</sup> up to 75°C) by using two different spindles; an 8 mm and a 25 mm in diameter for samples that have a height of 2 mm and 1 mm for low and high temperatures, respectively. The testing frequencies ranged from 0.1592 Hz to 15.92 Hz. In addition, DSR was used to conduct multiple stress creep and recovery (MSCR) at a temperature of 64°C by using a 25 mm diameter spindle with the thickness of 1 mm. In MSCR test, twenty cycles were used with one second of a loading time and nine seconds off-loading and the test was carried out using two stress levels 100 Pa and 3200 Pa [23].

**2.4. Artificial Intelligence Modelling and Analysis.** In addition to the mechanical empirical evaluation of the base and modified asphalt binders, current study proposed artificial intelligence research methods, namely, artificial neural networks (ANN) and support vector machines (SVM) as predictive models for the estimation of high and intermediate temperature performance characteristics of asphalt binders. The database for the artificial intelligence modelling was built by using the outcomes of the mechanical tests conducted under laboratory conditions. The data points were firstly normalized in order to improve data integrity and reduce data redundancy and MATLAB 2019b, MathWorks was used to develop the ANN and SVM models.

The ANN is a system for processing data by mimicking the idea of the way biological neurons work in a human brain. The ANN is composed of highly interconnected processing constituents called artificial neurons, which

operate in parallel logic and transmit information from one layer to others in serial operations [24]. Information is processed at the neurons, and the signals are passed through connection links, which are associated with weight vectors that determine the strength of the connections. The functions of these neurons are the first to sum up all the initially assigned weights from the lower layers and then to process the sum by a linear or nonlinear activation function to determine the output signal from the given input signals [25]. According to Venudharan and Biligiri [13], pure-linear function is categorized as linear, whereas hyperbolic tangent and logarithmic-sigmoidal functions are classified as nonlinear activation functions. As adopted in this study, hyperbolic tangent activation function is given in the following equation.

$$y_j = \frac{2}{1 + e^{-2s_j}}, \quad (1)$$

where  $s_j$  = input  $j$ th neuron,  $y_j$  = output  $j$ th neuron.

This type of machine learning method is referred to as a feed-forward neural network model (FFNNM) and it is adopted in the current study due to its efficiency in generalization [26]. As illustrated in Figure 1, the structure of the neural network was composed of three main layers, namely, the input layer, a hidden layer, and the output layer where the flow of information was from the input layer to the output layer. FFNNM was utilized with a backpropagation method where the aim was to find the optimum weights as an iterative process to minimize the error between the target and computed outputs with a selected accuracy [27].

A number of alternative ANN model structures were developed with 762 set of data points collected from the experimental investigations. The dataset was randomly divided as the training, validation, and testing. The training dataset was used for fitting the model. The validation dataset was used to provide an unbiased evaluation of the model fit and to adjust the model hyperparameters. Herein,  $K$ -fold cross validation technique was utilized to minimize the bias and variance [28]. Finally, the test dataset was used in the evaluation of model performance by using untrained dataset.

Two different scenarios were modelled based on the experimental outcomes for  $G^*$  and  $\delta$  of base and modified asphalt binders. Levenberg–Marquardt (LVM) was the training algorithm adopted in the ANN modeling. The input parameters ( $x_i$ ) considered to have influence on the target parameters were the mechanical test conditions, temperature ( $T$ ) and frequency ( $F$ ) for both models. The output

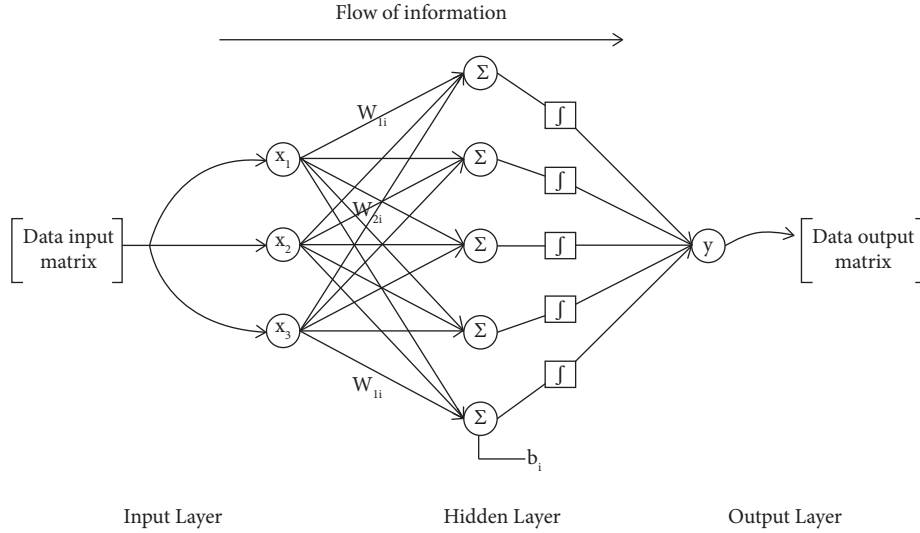


FIGURE 1: Schematic diagram of FFNNM with backpropagation network.

parameters ( $y_i$ ) were  $G^*$  and  $\delta$  for scenario 1 and scenario 2, respectively. The approach to find the optimum model was employed by the trial and error method by using different ANN architectures.

Support Vector Machines (SVM) is another significant computational modelling tool that has been used in solving numerous engineering problems including classification and regression. The aim of this technique is to learn the boundaries between the two classes through mapping the inputs to a high dimensional region. Initially, SVM's were used as a classifier for character and object recognition tasks; however, more recently the technique has also been proven to be effective in regression and time series prediction applications. SVM modelling technique has been derived from the statistical learning theory which has a number of distinct characteristics as compared to the traditional neural networks such as using a set of linear functions defined in a high dimensional space, carrying out risk minimization by using the loss function, and utilizing a risk function which consists of the empirical error and a regularization term which is derived from structural risk minimization (SRM).

Assuming that, the dataset includes  $D = ((x_i, y_i), i = 1, 2, \dots, n)$  where  $x_i$  is the input and  $y_i$  is the output parameters, the optimum SVM function is expressed as follows.

$$y = f(x) = w\varphi(x) + b, \quad (2)$$

where  $w$  is the weight factor,  $\varphi(x)$  represents the activation function, and  $b$  is the bias.

The accuracy of the proposed model relies on the minimization of the regularized risk function, which is as expressed as follows .

$$R(w) = \frac{1}{2}\|w\|^2 + C \frac{1}{n} \sum_{i=1}^n L_{\varepsilon}(y, f(x)). \quad (3)$$

With  $\varepsilon$ -insensitive loss function,

$$L_{\varepsilon}(y, f(x)) = \begin{cases} |y - f(x)| - \varepsilon, & \text{for } |y - f(x)| \geq \varepsilon, \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where the first term  $1/2\|w\|^2$  measures the flatness of the function, and the second term  $C1/n \sum_{i=1}^n L_{\varepsilon}(y, f(x))$  is the empirical error. The regularization parameter  $C$  determines the trade-off between the empirical error and the flatness of the model.

In other words, the suitable selection of user-defined parameters, which are regularization parameter  $C$ , radius of insensitive tube  $\varepsilon$ , and the parameter of RBF kernel function  $\gamma$  is crucially important to improve the model accuracy. Regularization parameter  $C$  controls the approximate function smoothness or flatness for the SVM where higher values of  $C$  represents higher penalty of errors and vice versa. Another parameter that controls the accuracy of the approximation function is the  $\varepsilon$  parameter which has significant effects on the number of support vectors. The  $\varepsilon$  parameter smoothens or complexifies the approximate function where a smaller value of  $\varepsilon$  leads to less support vectors and results in less complex learning machines and vice versa.

The SVM modelling approach adopts the idea of kernel functions. Herein, the radial basis kernel function (RBF) as expressed in equation (5) was utilized.

$$K(M, N) = \left( e^{-\gamma \|M - N\|^2} \right), \quad (5)$$

where  $K$  is the kernel,  $M$  is the training input,  $N$  is the unlabeled input, and  $\gamma$  is the kernel specific parameter.

In order to select the most suitable user-defined parameters, the manual method involving larger number of trials was used. Parameters combination resulting in the smallest value of root mean squared error (RMSE) and higher value of coefficient of determination ( $R^2$ ) was selected.

After developing both prediction models by using the ANN and SVM, the systematic evaluation of the model efficiencies was performed in conjunction with statistical performance indicator metrics. Model prediction capacity with training and the testing datasets were evaluated by performance indicator metrics, which were mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination ( $R^2$ ) as given in the following equations.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{\gamma}_i - \gamma_i)^2}, \quad (6)$$

$$R^2 = 1 - \left[ \frac{(\gamma - \hat{\gamma})^2}{(\gamma - \gamma_{\text{mean}})^2} \right], \quad (7)$$

where  $\hat{\gamma}_i$  is the  $i$ th experimentally observed data and  $\gamma_i$  is the  $i$ th target data predicted by the ANN and SVM models.

### 3. Results and Discussion

**3.1. Effects of Nanoparticles on Physical Properties.** The influences of nanoparticles on the physical properties of modified binders were illustrated in Figure 2. It was noted that, modified binders have higher stiffness compared to the base binder as the penetration values were declined and the softening point values were risen. The reduction in penetration was nearly 63% for 5%  $\text{Al}_2\text{O}_3$  and 60% for 3%  $\text{Al}_2\text{O}_3$ . At 7%  $\text{Al}_2\text{O}_3$ , the modified binders have shown a different reaction as the reduction in penetration was slightly less than 3 and 5% concentrations but higher than the base asphalt with a reduction of penetration around 45%. As a response to the reduction in penetration, the softening points of modified asphalt binders were improved by nearly 15% for 5%  $\text{Al}_2\text{O}_3$ , followed by 11% increment for 3% and 7%  $\text{Al}_2\text{O}_3$  modified binders. In addition, the effects of  $\text{Al}_2\text{O}_3$  nanoparticles on the viscosity of modified binders at different temperatures are shown in Figure 3. The Superpave requires that the viscosity of asphalt binders must not be more than 3 Pa·s at 135°C. It was noted that all of the asphalt binders passed the requirement of the Superpave method as the highest number among the blends was 1.04 Pa·s at 135°C for 7%  $\text{Al}_2\text{O}_3$  while lowest viscosity noted to be for the base asphalt binder which was 0.50 Pa·s. The additional increment of the modifier content led to a rise in the viscosity value which was an expected outcome since the modification process has led to an increase in stiffness for the asphalt binders.

#### 3.2. Experimental Results of Rheological Properties

**3.2.1. Effects of Nanoparticles on the Isochronal Plots.** The isochronal plots which represent stiffness and elasticity of binders at various temperatures and at a frequency of 1.592 (10 rad/s) are demonstrated in Figures 4 and 5, respectively. The results showed that the base asphalt binder has the lowest stiffness and the highest elasticity, 5%  $\text{Al}_2\text{O}_3$  has the

maximum stiffness and the minimum elasticity among the blends while this was followed by 7%  $\text{Al}_2\text{O}_3$  and 3%  $\text{Al}_2\text{O}_3$  of the modifier contents. The results indicated that 5% of  $\text{Al}_2\text{O}_3$  has the optimum viscoelastic properties among the blends. In addition, the highest complex modulus resulted in higher stability under permanent deformation at high temperatures, whereas the lower phase angle indicated to a higher resistance to thermal cracking at low temperatures. It is noteworthy to mention that, 7%  $\text{Al}_2\text{O}_3$  showed a different behavior as the complex modulus was decreased and the phase angle was enhanced at the same time compared to 5%  $\text{Al}_2\text{O}_3$ . This might be due to the occurrence of agglomeration among the nanoparticles during the mixing process which have affected the dispersion of nanoparticles in the asphalt matrix [11].

**3.2.2. Effects of Nanoparticles on the Master Curves.** To better characterize and understand the rheological performance of nanoparticles-modified asphalt binders, a master curve was constructed. A master curve is a representation of stiffness ( $G^*$ ) and elastic modulus ( $\delta$ ) over a range of temperatures and frequencies by using convenient shifting factors. The reference temperature ( $T_{\text{ref}}$ ) was 25°C and data points at other temperatures were shifted horizontally to construct a single curve. Figure 6 illustrates the master curves of  $G^*$  and  $\delta$  for the base and modified asphalt binders. The greater stiffness and elasticity denoted that, the binder has superior viscoelastic properties which indicated better resistance to permanent deformation and fatigue cracking at elevated temperatures and low temperatures. Figure 6 demonstrates that, the base asphalt has the highest elasticity and the lowest stiffness, while 5%  $\text{Al}_2\text{O}_3$  has the lowest elasticity and highest stiffness among the blends. Based on the results revealed by the master curves, it can be concluded that 5%  $\text{Al}_2\text{O}_3$  can be considered as the optimum concentration for the modification process particularly at high temperatures although the improvement in high temperature performance characteristics was at the expense of losing elastic characteristics for the modified asphalt binders.

**3.2.3. Effects of Nanoparticles on High Temperatures Permanent Deformation.** Bitumen is a thermoplastic material that performs as solid and liquid at low and high temperatures, respectively. The permanent deformation (rutting) is one of the effects of the most common issue of the pavement at elevated temperatures, and the ASTM revealed that to stand with this issue, the bitumen (unaged) must have permanent deformation more than or equal to 1 kPa. The effects of rutting on base and modified binders are displayed in Figure 7. It was noted that, the modified binders have less temperature susceptibility compared to the base binder. This indicated that the modification of bitumen using nanoparticles can reduce the permanent deformation and increase the service life of the pavement. The best performance at 65°C was achieved by 5%  $\text{Al}_2\text{O}_3$  concentration with enhancement up to 210%, which was followed by 7% and 3%  $\text{Al}_2\text{O}_3$  with improvements around 118% and 44%,

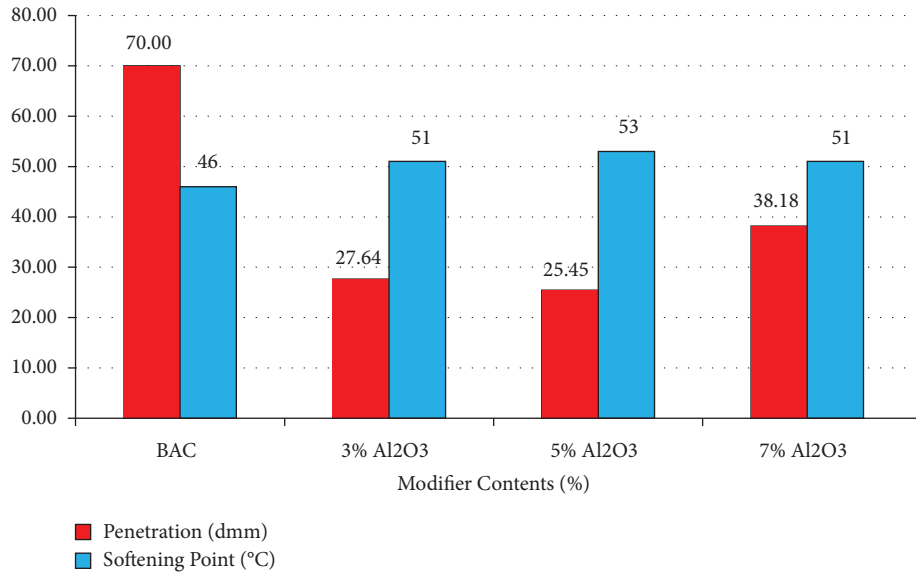


FIGURE 2: Influences of nanoparticles on the penetration and softening points of modified asphalt binders.

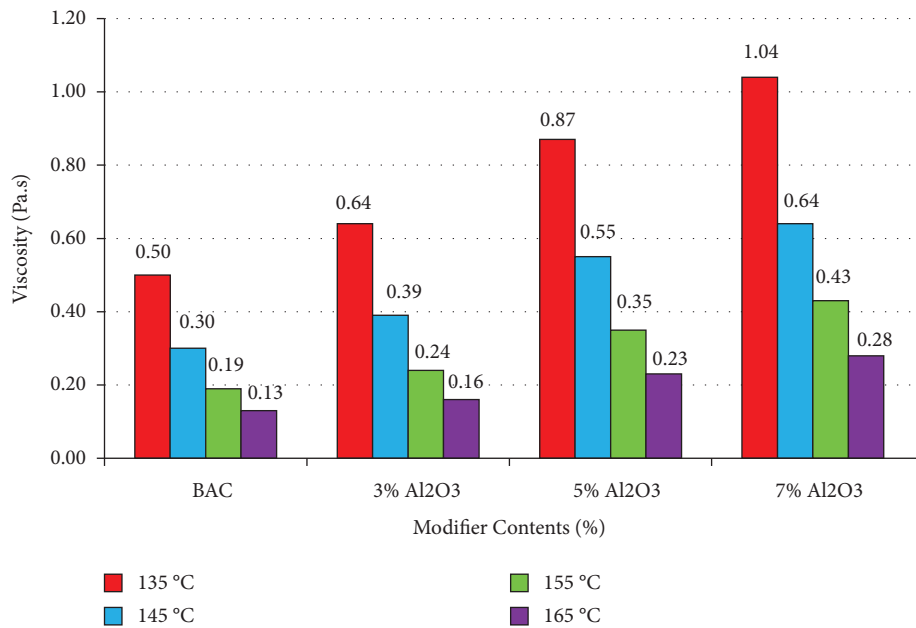


FIGURE 3: The influence of nanoparticles on the viscosity of asphalt binders.

respectively. Moreover, all the blends passed the requirements of Superpave at 65°C while the 5% Al<sub>2</sub>O<sub>3</sub> has also passed it at 75°C.

**3.2.4. Effects of Nanoparticles on Low Temperatures Thermal Cracking.** The Superpave technique considered 5000 Pa as the maximum limit for fatigue-cracking at low and intermediate temperatures. Figure 8 illustrates the influence of nanoparticles on the fatigue resistance parameter for base and modified binders. The results showed that, the modified asphalt binders have higher stiffness in comparison with the base asphalt binder which was designated as the base asphalt

and has better elastic properties compared with the modified binders. Moreover, nanoparticles have a significant effect on visco-properties, and it does not have an excellent impact on elastic properties, but all binders were within the specification of Superpave which is less than 5000 Pa at 25°C.

**3.2.5. Effects of Nanoparticles on the MSCR.** MSCR test was used to simulate the movement of traffic flow on the highway surface and to evaluate the resistance and recovery of asphalt binder to rutting after the applied loads are removed [29]. Figure 9 presents the results of MSCR for the base and modified asphalt binders under stress levels of 100 and

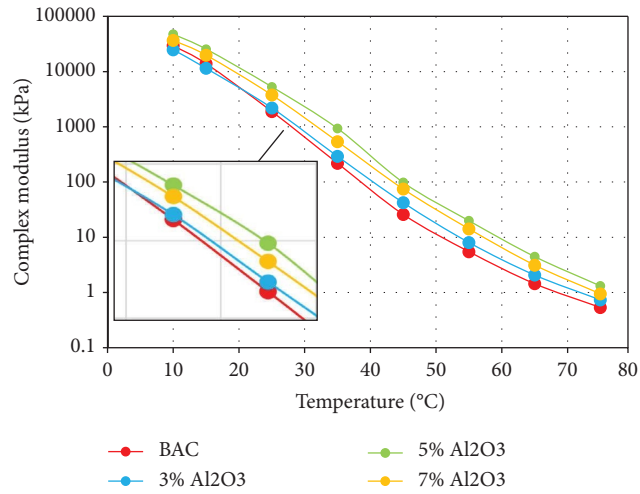


FIGURE 4: Isochronal plot for  $G^*$  of base and modified asphalt binders.

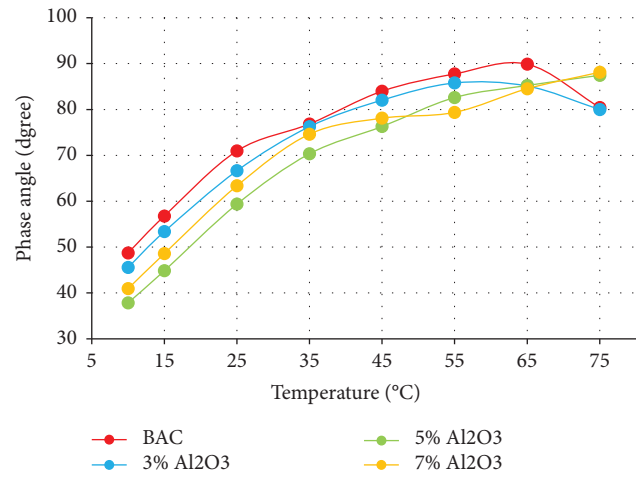


FIGURE 5: The isochronal plot for  $\delta$  of the base and modified asphalt binders.

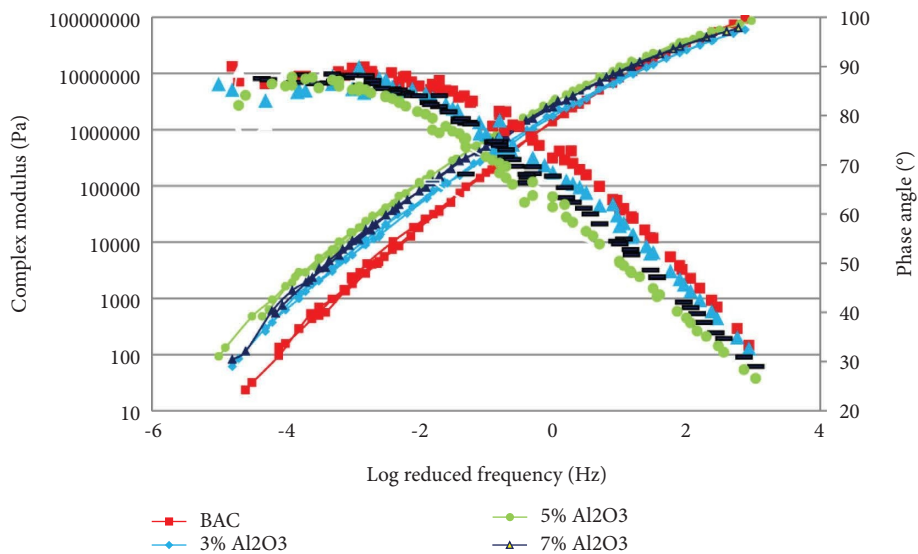


FIGURE 6: The effects of the modifier on the phase angle and complex modulus of AC.



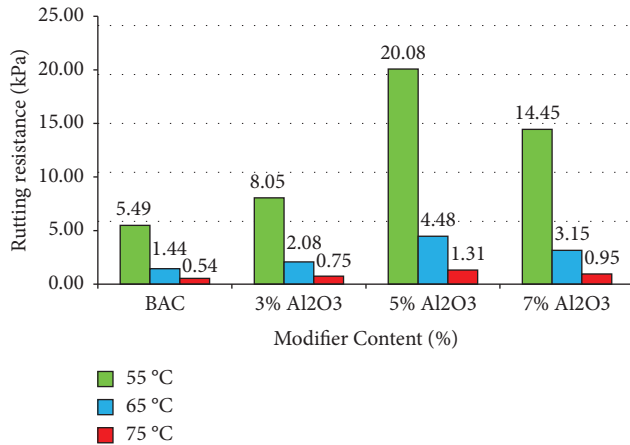


FIGURE 7: The effects of rutting on base and modified binders.

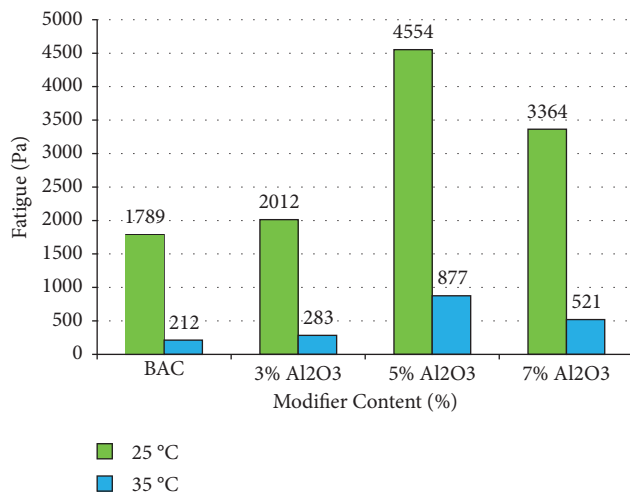


FIGURE 8: The effects of fatigue on base and modified binders.

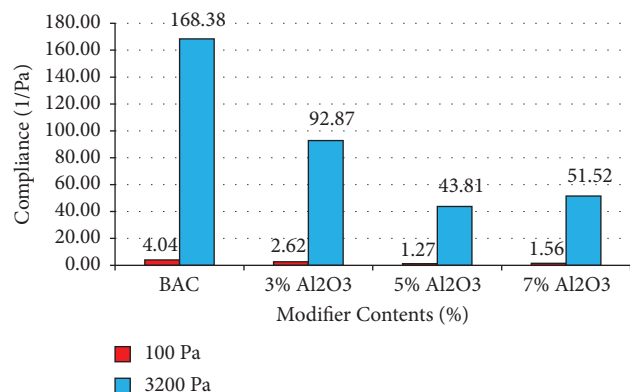


FIGURE 9: MSCR for the base and modified asphalt binders under stress levels of 100 and 3200 Pa.

3200 Pa. It was found that the binder with 5% Al<sub>2</sub>O<sub>3</sub> has the maximum effect on the permanent deformation at elevated temperatures at both levels. The improvement in creep compliances were 1.27 and 43.81 Pa at 100 and 3200 Pa,

respectively. The reduction of the creep compliance parameter was also anticipated from the increase in hardness of modified asphalt binders as observed from the physical tests. Meanwhile, the base asphalt binder has the maximum sensitivity to permanent deformation at high temperatures with compliance values of 4.04, 168.38 Pa for both stress levels respectively. In addition, the improvements in resistance of permanent deformation were 35% and 44% for 3% Al<sub>2</sub>O<sub>3</sub> and 69% and 73% for 5% Al<sub>2</sub>O<sub>3</sub> and 61% and 69% for 7% Al<sub>2</sub>O<sub>3</sub> at 100 and 3200 Pa individually.

**3.3. Artificial Intelligence Model Results.** Support vector machines (SVM) and artificial neural network (ANN) models were developed by using MATLAB (MathWorks Inc R2019b). Dataset included 852 data points from the mechanical test conditions (testing temperature and loading frequency) as the input parameters and the  $G^*$  and  $\delta$  as the output parameters. A total of four individual models were constructed to predict two different outputs;  $G^*$  and  $\delta$  by using two different modelling techniques; ANN (model 1 and model 2) and SVM (model 3 and model 4, respectively).

A number of different ANN architectures with different learning algorithms, activation functions, and a various number of hidden neuron layers were trained iteratively to find the best performing network structure. The optimum model was obtained by using the Levenberg Marquadt (LM) learning algorithm with two inputs, three hidden neurons, and one output topology. The network utilized backpropagation method to minimize the errors in prediction and the activation function was selected as the hyperbolic tangent activation function. On the other hand, the radial basis kernel function was utilized for the model development by the SVM. After setting the suitable user-defined parameters, the 10-fold cross validation technique was utilized to improve model prediction accuracy. By using this technique, the data points were divided into ten different sets. Each algorithm was then trained by using nine of the sets and evaluated using the tenth set. This process was repeated 10 times and each time a different set was used for testing. The mean of the predictions from ten different models were then used to evaluate the performance of the algorithm.

The statistical metrics utilized in this study to evaluate the model efficiency were the coefficient of determination ( $R^2$ ) and the root mean squared error (RMSE). Figure 10 illustrates the best performing networks for predicting targets of  $G^*$  and  $\delta$  with training datasets based on  $R^2$ . The  $R^2$  values close to +1 indicated that, the model has high capacity for predicting the experimental outcomes. From Figure 10, it was observed that, the ANN model slightly performed better than the SVM model for predicting the  $G^*$  while the SVM model outperformed the ANN model in predicting the experimentally observed  $\delta$  with the training datasets.

On the other hand, it should be noted that, a smaller difference between the  $R^2$  values obtained for the training and testing datasets is significantly important in order to avoid model overfitting. On this basis, the model



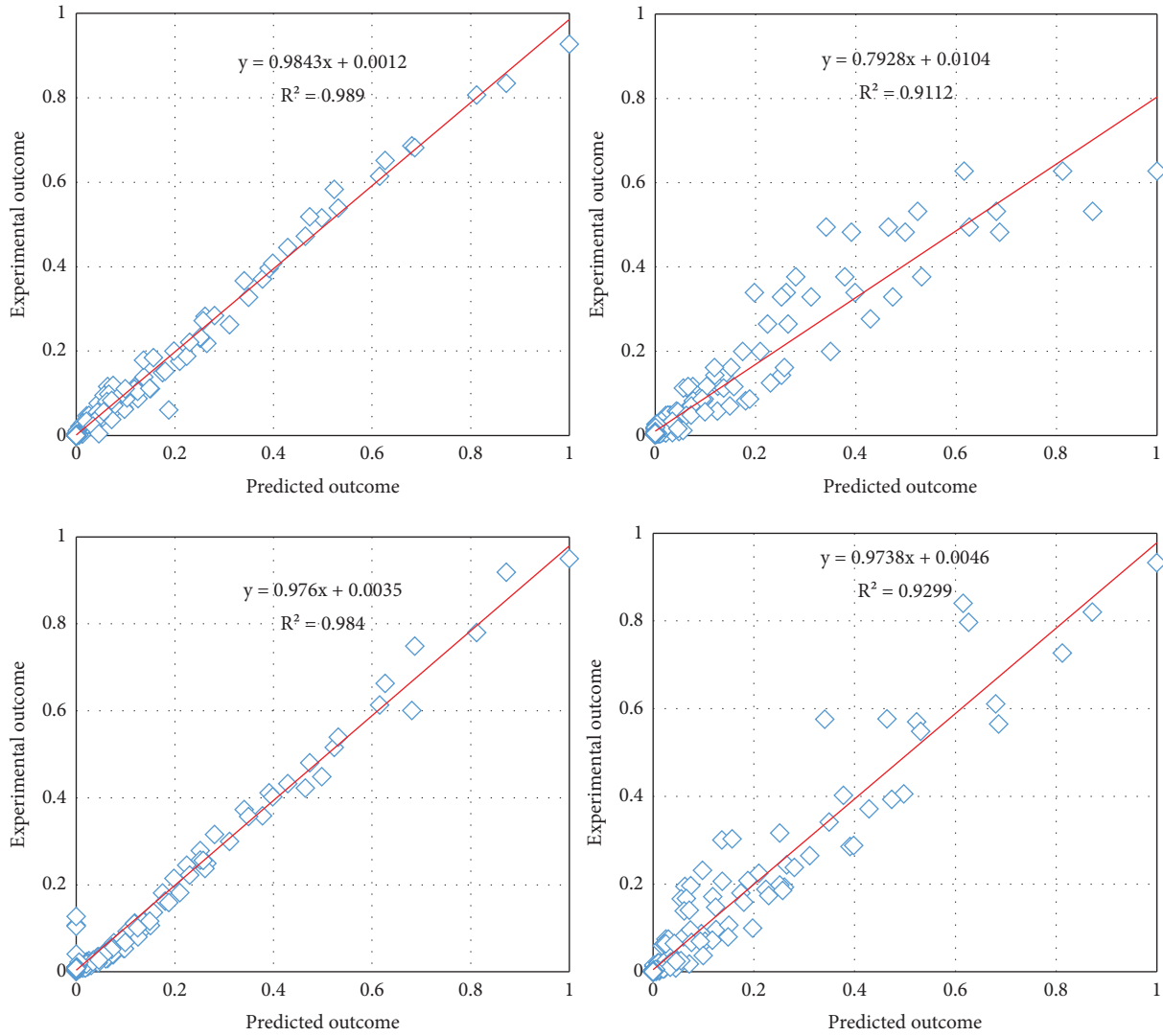


FIGURE 10: The measures of goodness of fit for (a) ANN  $G^*$  prediction, (b) ANN  $\delta$  prediction and SVM, (c) SVM  $G^*$  prediction, and (d) SVM  $\delta$  prediction model results.

TABLE 2: ANN and SVM model results for  $G^*$  and  $\delta$  prediction.

	Model 1: ANN model for $G^*$ prediction		Model 2: ANN model for $\delta$ prediction		Model 3: SVM model for $G^*$ prediction		Model 4: SVM model for $\delta$ prediction	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
$R^2$	0.989	0.873	0.911	0.816	0.984	0.952	0.929	0.861
RMSE	0.017	0.060	0.054	0.107	0.021	0.041	0.045	0.091

performances with the training and testing datasets are presented in Table 2. It was observed that the  $R^2$  obtained for model 1 was 0.989 and 0.873 for training and testing datasets and 0.911 and 0.816 for model 2, respectively. On the other hand, for the SVM models, the  $R^2$  for training and testing datasets were 0.984 and 0.952 for model 3 and 0.929 and 0.861 for model 4, respectively. Based on these results, it was concluded that a smaller gap between the training and testing datasets for the SVM models suggested that those models have not suffered from the overfitting phenomenon

which could have negatively affect the performance of the models for untrained datasets.

Moreover, besides evaluating the model performance by the  $R^2$ , the residuals distribution of the models have significant influence on the model prediction performance. On this basis the RMSE values for the models are also computed and tabulated in Table 2. A smaller RMSE value indicated smaller distribution of the errors and therefore resulted in better performing models. From Table 1, it was observed that the smallest RMSE values for the testing datasets were

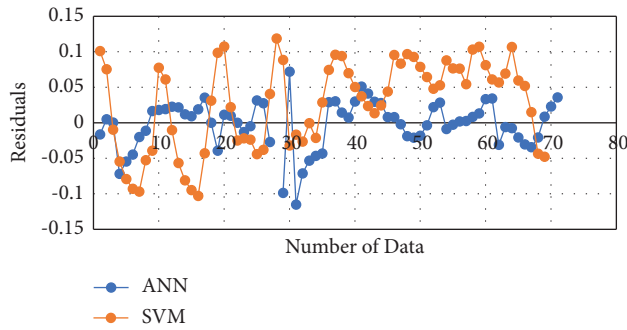


FIGURE 11: Residual distributions for ANN and SVM models for predicting  $G^*$ .

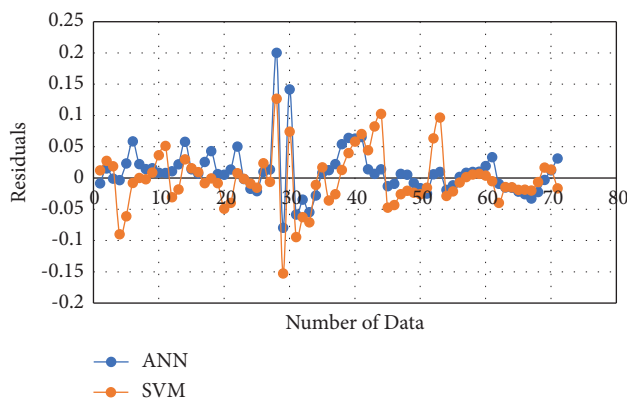


FIGURE 12: Residual distributions for ANN and SVM models for predicting  $\delta$ .

obtained by the model 3 where the RMSE was 0.041 and the highest RMSE was obtained for model 2 with 0.107.

In addition, considering that high  $R^2$  values do not always mean a good regression model, the residual distribution test decides whether the selected model is suitable for describing the empirical data, or if another model is required [30]. The residuals distribution of the two models by using the testing datasets for predicting the  $G^*$  and  $\delta$  are shown in Figures 11 and 12, respectively. As observed from both the figures, in the SVM model, the residual variations were minimal and consistent, while the deviance in the ANN was significantly larger than in the SVM models.

#### 4. Conclusion

The physical properties and rheological performance characteristics of aluminum oxide nanoparticle- modified asphalt binder were investigated by using conventional and DSR testing procedures. Heuristic modelling techniques were utilized to predicting the experimental outcomes namely,  $G^*$  and  $\delta$  from the mechanical testing conditions, testing temperatures and frequencies. Based on the mechanical test results and the heuristic analysis to predict the experimental outcomes, the following conclusions were drawn.

- (i) The investigation of rheological properties shows an increase in the complex modulus and decline in the phase angle, indicating better viscoelastic properties which led to mitigate the asphalt distress.
- (ii) Nanoparticles can increase the hardness of modified binders which reduce the rutting effects at high temperatures, but it has lacked the effects at low temperatures due to low elastic characteristics.
- (iii) Both ANN and SVM models were able to predict the targeted outputs,  $G^*$  and  $\delta$ , accurately while SVM models were able to capture the nonlinear relationship in the dataset and was shown to be more efficient in predicting the untrained data points.

#### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

#### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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