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Research Paper

Application of Conventional Mathematical and Soft Computing Models for Determining the Effects of Extended Aging on Rutting Properties of Asphalt Mixtures

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Abstract

Pavement performance prediction is a mounting task due to the many varied influencing factors particularly aging which varies with time, weather, production, type of pavement and etc. This paper presents a conventional mathematical model named Superpave model, Artificial Neural Network (ANN), and Supporting Vector Machine (SVM) techniques to predict the effects of extended aging on asphalt mixture performance measured in terms of rutting properties determined from the dynamic creep test. The accuracy of each method was compared to select the most reliable technique that can be used to forecast the rutting behavior of asphalt mixtures subjected to different aging conditions. The results indicated that the Superpave model was only reliable at lower temperatures, while ANN and SVM techniques showed the capability of precise prediction under all conditions. The overall results showed that the ANN was the most promising technique that can be adopted to satisfactorily forecast the effects of aging on rutting properties of all mixtures. The developed model can be embraced by the pavement management sector for more precise estimation of the pavement life cycle subjected to different aging conditions which can be used to design efficient pavement maintenance and rehabilitation plans.

Keywords: Asphalt mixture aging; rutting; Superpave model; artificial neural network; supporting vector machine

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1. Introduction

Aging is one of the main factors that adversely influence pavement performance and durability. Its importance can be seen from the extensive research that has been carried out on the subject matter. Izadi et al. (2018) studied the impacts of aging on fatigue behavior of hot and warm mix asphalts and found that aging always increases fracture energy and failure resistance. Hamzah et al. (2015) studied the effects of extended aging duration on visco-elastic properties of binders and found that aging differs and depends on the binder type, test temperature, and aging conditions. Omranian et al. (2018a and b) explored the impacts of short-term aging on asphalt mixtures properties using image analysis and response surface method. It was reported that apart from the dominant impacts of aging temperature and duration; aging increment resulted in higher mixtures' fracture toughness and broken aggregates, while exhibited contradictory effects on adhesion failure. It was also reported that aging increased rutting resistance and resilient modulus, while reduced fatigue resistance. Julaganti et al. (2019) studied the rheological characteristics of polymer and crumb rubber modified binders subjected to different short-term aging temperatures. The results indicated that lower aging temperatures resulted in binder stiffness reduction which in turn reduced viscosity, complex modulus, and failure temperatures, while increased compliance in multiple stress creep recovery and phase angle. Hamzah and Omranian (2015) investigated the effects of short-term aging on pavement air voids during mixture transportation from plant to field. It was found that although aging during haulage slightly affects mixture properties, the impact on mixture compacted air voids was found to be statistically insignificant. The effects of aging on mixture permanent deformation or rutting had also been widely investigated.

In pavement engineering, rutting refers to the progressive accumulation of permanent deformation in each layer due to repeated traffic loading, which detrimentally affect pavement structure. In pavement maintenance, it is considered as one of the major surface distress. According to Yin et al. (2017), long-term aging significantly increases asphalt mixtures stiffness and rutting resistance. From the minimum strain rate master curve, Azari and Mohseni (2013) explored the effects of aging on asphalt mixture permanent deformation and found that temperature, tire pressure, and aging were the key factors influencing rut depth. It was also found that short-term and long-term aging of asphalt mixtures have a significant dependency.

Several mathematical models have been developed to predict rutting performance. Daniel et al. (2005) used a creep compliance master curve to compare the performance of asphalt mixtures containing different percentages of reclaimed asphalt. The creep master curves for each mixture were fitted using a modified power law (MPL) to describe the mean value of mixture compressive creep compliance. The results showed that the creep compliance curves for mixtures with increasing percentages of RAP follow the same trend as mixtures subjected to various levels of aging. In another study, Zhao et al. (2012) developed a multivariate linear regression model to evaluate the effects of voids in total mix (VTM), $G^*/\sin\delta$, warm additive type, and temperature on rutting performance of warm mix asphalt. Zhou et al. (2004) attempted to develop a precise mathematical model for three parts of the creep curve obtained from the dynamic creep test using an algorithm to calculate the boundary point for each phase of creep. According to Mehrara and Khodii (2010), this model provides a means for detecting permanent deformation or estimating the probable deformations for a given number of load cycles. Table 1 summarizes some initial rutting models found in the literature.

Table 1. Mathematical equations for rutting models [Zhou et al., 2004].

No.	Model	Mathematical Equations	Developed by
1	Semi-log model	$\varepsilon_p = a_1 + b_1 \, Log \, N$	[Barksdale, 1972]
2	Power law model	$\varepsilon_p = aN^b$	[Monismith et al. 1975]
3	VESYS model	$\varepsilon_{pn} = \mu . \varepsilon_r \, N^{-\alpha}$	[Kenis, 1977]
4	Ohio State model	$\varepsilon_p = aN^{(1-m)}$	[Majidzadeh et al., 1980]
5	Superpave model	$Log \, \varepsilon_p = Log \, \varepsilon_p \, (1) + S \, (LogN)$	[Lytton et al., 1993]

Note: ε_p = accumulated permanent strain; N = number of load repetitions; ε_{pn} = permanent strain due to a single load application; ε_r = resilient strain; ε_p (1) = the permanent strain at the first load application; a, b, m, and S = positive regression constants; μ = permanent deformation parameter; α=1-b = permanent deformation parameter.

Although aging has been extensively studied, its complex effects on mixture behavior cannot be conveyed in mathematical terms or expressed in a concise relationship. Hence, new models have emerged using modern pattern recognition techniques. One example is artificial neural network (ANN). Unlike conventional regression analysis and mathematical models, ANN is able to recognize trends in the data pattern. ANN is a computer technique that attempts to simulate some important features of the human nervous system. It has the capacity to solve problems by applying information gained from past experiences to new problems or specific scenarios. Analogous to the human brain, ANN uses many simple computational elements, named artificial neurons, connected by variable weights [Haykin, 2001]. A summation and transfer functions of a typical artificial neuron are illustrated in Figure 1. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. The network is adjusted based on a comparison of the output and the target until the network output matches the target.

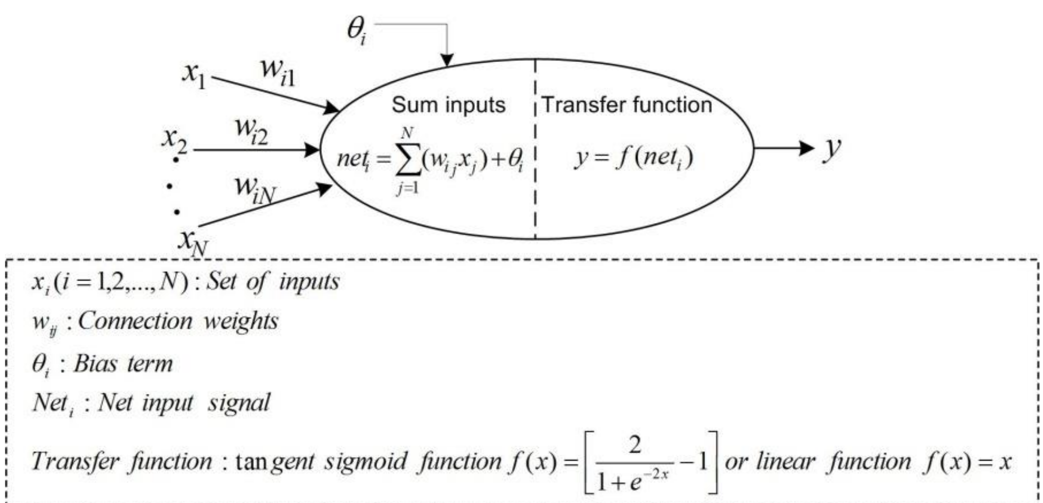

Figure 1. Summation and transfer functions of a typical artificial neuron [Ghanizadeh and Fakhri, 2014].

ANN technique has been widely used in pavement engineering to determine the relationships between various parameters such as properties of asphalt mixture components, mixture production methods, and environmental conditions with pavement performance. Sakhaei Far et al. (2009) developed ANN to predict the dynamic modulus of hot mix asphalt during long-term performance in service and the results showed a good agreement between measured and predicted values. Ghanizadeh and Ahadi (2015) employed ANN to study pavement structure flexibility and its critical responses when subjected to axle loadings. A Feed-Forward back propagation neural network was used to predict the response. The predicted results obtained from ANN indicated great precision. The ANN also exhibited superb capability to reduce time consumption for predicting fatigue life and rutting. Yan and You (2014) studied the complex modulus of asphalt mastics using ANN. Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Pola-Ribiere Conjugate Gradient (CGP) algorithms were used to train ANN. The results showed that LM was the best algorithm to train ANN. It was also found that ANN was a fast and excellent technique to evaluate complex modulus of asphalt mastics. Kırbaş and Karaşahin (2016) employed three different models including deterministic regression analysis, multivariate adaptive regression splines (MARS), and ANN to predict pavement deterioration in terms of pavement condition index (PCI). According to their findings, although all models exhibited comparable prediction, the ANN model was found to be more accurate.

The Support Vector Machine (SVM) is another computer technique that can predict asphalt mixtures performance by applying information obtained from past investigations. The SVM has also been used in pavement engineering. Gopalakrishnan and Kim (2010) used the SVM approach to predict the dynamic modulus of HMAs. The SVM superiority over ANN and Genetic Programming (GP) (in terms of accuracy) to predict the fatigue life of Polyethylene Terephthalate (PET) modified asphalt mixture was reported by Moghaddam et al. (2016). The successful utilization of SVM to predict indirect tensile strength of foamed bitumen-stabilized base course as well as critical responses of flexible pavements was also reported by Nazemi and Heidaripanah (2016) and Ghanizadeh (2017), respectively. Although ANN and SVM techniques have been used extensively to predict different areas of pavement engineering, not much work has been carried out on the application of these techniques to predict the effects of aging on the permanent deformation of asphalt mixture. Accurate prediction of pavement permanent deformation is a very essential task for the pavement management and rehabilitation industry. This paper explores and compares the implication of two artificial intelligence techniques known as ANN and SVM to model the effects of extended aging durations on the rutting properties of asphalt mixture. Comparison of ANN and SVM with existing mathematical models to model the cumulative strains obtained from dynamic creep tests, is also presented. The best-developed model can then be used by the management sector to estimate the pavement service life at different aging levels and make essential plans for pavement maintenance.

2. Materials and Methods

2.1 Materials

In this study a PG-64 binder supplied by Petronas was used and its properties are shown in Table 2. The granite aggregate was supplied by Kuad Quarry Sdn. Bhd. Table 3 presents aggregate properties. The median aggregate gradation was used in accordance with the Malaysian Public Works Department specifications for asphalt mixture type AC14 (Table 4) [PWD, 2008].

Table 2. Binder properties.

Aging Stage	Test Parameters	Value	Standard
Un-aged	Penetration at 25 °C (dmm)	80	ASTM D 5

Aging Stage	Test Parameters	Value	Standard
	Softening point (°C)	46	ASTM D 36
	Ductility at 25 °C (cm)	>100	ASTM D 113
	G*Sinδ at 64 °C (Pa)	1342	ASTM D 7175
	Viscosity at 135 °C (Cp)	300	ASTM D 4402
Short-Term Aged	G*Sinδ at 64 °C (Pa)	3090	ASTM D 7175
	Viscosity at 135 °C (Cp)	475	ASTM D 4402

Table 3. Aggregate properties.

Property	Test Result	Test Method
Coarse aggregates bulk specific gravity	2.62	AASHTO T85
WATER Absorption (%)	0.40	AASHTO T85
Fine aggregates bulk specific gravity	2.57	AASHTO T84
Absorption (%)	0.54	AASHTO T84
Fine aggregate angularity (%)	47.3	AASHTO T33 (Method A)
Course aggregate angularity (%)	49.5	AASHTO TP56 (Method A)
Flat and elongated (%)	23.3	BS 812-105
Los Angeles abrasion (%)	23.86	AASHTO T96
Aggregate crushing value (%)	19.25	BS 812-110

Table 4. Aggregate gradation used in this study.

Sieve size (mm)	Percentage passing by weight		
	Lower limit	Median	Upper limit
20	100	100	100
14	90	95	100
10	76	81	86
5	50	56	62
3.35	40	47	54
1.18	18	26	34
0.425	12	18	24
0.150	6	10	14
0.075	4	6	8

To produce mixture in the laboratory, the binder and batched aggregates were mixed at temperatures ranging from 155 to 165˚C. Mixing took about one minute to ensure that aggregates were sufficiently coated with binder. The loose mixtures were then placed inside a conventional oven for 0, 2, 4, and 8 hours to artificially age the samples. The oven was set at 135 ℃ following AASHTO-R30 procedures. In the meantime, the loose mixtures were overturned after every one hour to ensure they were aged homogeneously. For specimen compaction, the Servopac gyratory compactor was used to better simulate the action of the field roller compactor.

2.2 Dynamic Creep Test

The dynamic creep test was conducted to estimate the rutting potential of asphalt mixtures subjected to different short-term aging conditions under constant repeated stress. The resistance to rutting and permanent deformation were determined by the application of dynamic loading on the specimen. The test was conducted in accordance with NCHRP 9-19 SUPERPAVE procedures using THE Universal Testing Machine (MATTA) [Witczak et al., 2002]. To conduct the dynamic creep test, a cylindrical specimen with approximately 4% air voids was placed in the controlled temperature chamber at 40, 50, and 60˚C for at least 4 hours prior to ~~the~~ testing. The test parameters used are shown in Table 5. The load was applied to the specimen until it exceeded either the specimen bearing load limitation when it fractured or reached the 10000th cycle.

2.3 Modeling

2.3.1 Deterministic Modeling

Deterministic or regression base modeling is the conventional method used to predict pavement behavior. In this study, the Superpave model was employed to predict the effects of aging on mixture rutting properties as shown in Eq. (1) [Lytton et al., 1993]. The model was used to predict accumulated permanent strain of mixtures subjected to different aging conditions.

$$\log \varepsilon_p = \log\ \varepsilon_p(1) + S(Log\ N) \qquad (1)$$

where ε_p is accumulated permanent strain, $\varepsilon_p(1)$ is the permanent strain at the first load application, S is regression constant, and N is the number of load repetitions.

2.3.2 Soft Computing Modeling

2.3.2.1 Modeling by Artificial Neural Network

ANN is a robust computational technique which has the capability to predict the complex relationships between multiple variables. In this study, ANN was employed to establish the relationship between the number of cycles, aging level, and temperatures as input parameters and cumulative strain as an output. Matlab neural network (NN) toolbox was used for the training and validating of the ANN. Matlab NN toolbox randomly assigns the initial weights for each run each time which considerably changes the performance of the trained ANN even if all the parameters and ANN architecture are kept constant. This leads to extra difficulties in the selection of the optimal network architecture and parameter settings. To overcome this difficulty, a program was developed in Matlab which processed the trial and error procedure automatically. The program explored various numbers of the neurons (5, 10, 15, 20, 25, 30, 35, 40, 45 and 50) in the hidden layer for five times and the best ANN architecture with the minimum RMSE of the testing set was selected. The testing (30%), cross-validating (10%), and training (60%) sets for ANN training procedures were chosen randomly from the experimental dataset. The optimal ANN architecture was found to be 3-40-1 (40 hidden neurons) as shown in Figure 2. Subsequently, hyperbolic tangent sigmoid and linear transfer functions were employed for the hidden layer and output layer, respectively.

Table 5. Dynamic creep test parameters.

Parameters	Values
Pulse waveform	Haversine
Applied pulse width duration	100 ms
Rest period	900 ms
Stress during loading	207 kPa
Stress during rest period	9 kPa
Number of loading cycle	10000
Temperature	40, 50 and 60˚C

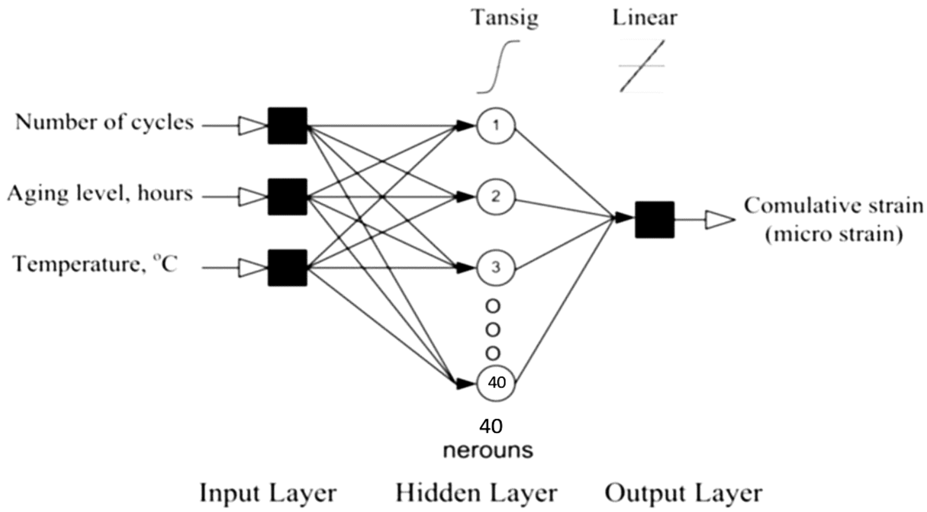

Figure 2. Optimal ANN architecture.

2.3.2.2 Modeling by Supporting Vector Machine

Support Vector Machine (SVM) is a well-known approach in the field of machine learning. It is usually employed as a tool for classification problems in a supervised learning framework. SVM can be also used for regression problems. To determine the regression using SVM, an estimation functional should be found to relate dependent variable y to a set of independent variables $x_i \in X$, $X = (x_1, x_2, \ldots, x_n)$. In general, the estimation function in SVM takes the form of Eq. (2) [Smola and Scholkopf, 2004].

$$f(X) = w.\phi(X) + b \qquad (2)$$

where, (·) denotes the inner product in **Ω**, a feature space of possibly different dimensionality such that $\phi : X \rightarrow \Omega$ and b∈R. ϕ is a kernel function.

The next stage is finding a functional form for f(x) that can correctly predict new cases that the SVM has not experienced before. This can be achieved by training the SVM model using a training set by minimizing the error function as shown in Eq. (3).

$$Min \quad Z = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i + C \sum_{i=1}^{N} \xi_i^* \qquad (3)$$

subject to the constraints:

$$w^T \phi(x_i) + b - y_i \le \varepsilon + \xi_i^*$$
$$yi - w^T \phi(x_i) - b \le \varepsilon + \xi_i$$
$$\xi_i^*, \xi_i^* \ge 0, \ i = 1,2,\ldots, N$$

where, w is the weight vector of the regression hyperplane, b is the threshold with respect to the origin, ε is the precision value, ξ_i and ξ_i^* are nonnegative slack variables representing the positive and negative errors, respectively, with absolute values larger than ε. The constant C is the capacity constant and is a non-negative regularization parameter that controls the tradeoff between achieving a low training error and a low testing error that is the ability to generalize the classifier to unseen data.

SVM only minimizes errors larger than ε. Figure 3 shows the concept of ε-insensitivity. As evidence, only data points outside the range $\pm\varepsilon$ have non-zero slack variables.

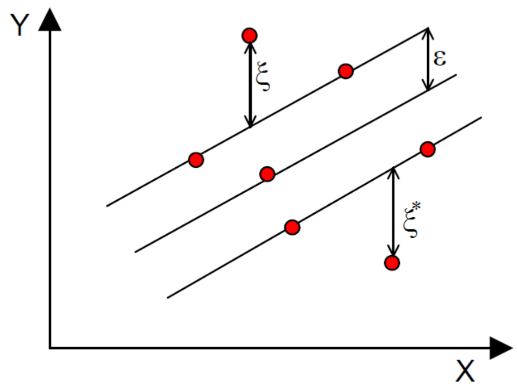

Figure 3. The concept of ε-insensitivity [Ghanizadeh, 2017].

Different kernels can be used in SVM models including linear, polynomial, radial basis function (RBF), and sigmoid. The RBF is the most popular choice of kernel types used for SVM models. This is mainly because of their localized and finite responses across the entire range of the real x-axis. In this study, RBF as shown in Eq. (4) was employed to develop the SVM model.

$$\phi(x_i, x_j) = e^{(-\gamma|x_i - x_j|)} \quad (4)$$

A regression SVM was trained and validated to compare the capability of SVM, ANN, and Superpave models. In order to develop the SVM model, input parameters were considered as the number of cycles, the aging level, and temperatures, and the cumulative strain was assumed as an output parameter. To assess the accuracy and also avoid over-fitting, 70 percent of records were considered as a training set and the remaining 30 percent as a testing set. Over-fitting is defined as the difference between accuracy on a training set versus a testing set which leads to large prediction errors.

C, γ, and ε are the parameters that may affect the SVM accuracy in case the RBF function is used as the kernel function. To attain the best prediction accuracy and identify the appropriate SVM, the parameters that give the best generalization were chosen from a trial and error process by checking the goodness of fitting of both training and testing sets. These values were determined to be 20, 10, and 0.01 for C, γ, and ε, respectively.

3. Results and Discussions

3.1 Database

Figures 4 to 6 illustrate the relationships between cumulative strain and the number of cycles for un-aged and artificially aged mixtures at 40, 50, and 60°C, respectively. the results consistently showed that extending the aging duration causes a reduction in cumulative strain, while an increase in the test temperature causes the cumulative strain to increase. For instance, the cumulative strain of artificially aged mixtures for 4 hours after 10000 cycles is approximately 4500 at 40°C. This value is higher compared to corresponding values of artificially aged mixture for 8 hours at the same stage. However, a 20°C increase in test temperature increases the cumulative strain of 4 hour artificially aged mixtures from approximately 4500 to approximately 15000. It implies that at higher temperatures, mixtures are more prone to permanent deformation.

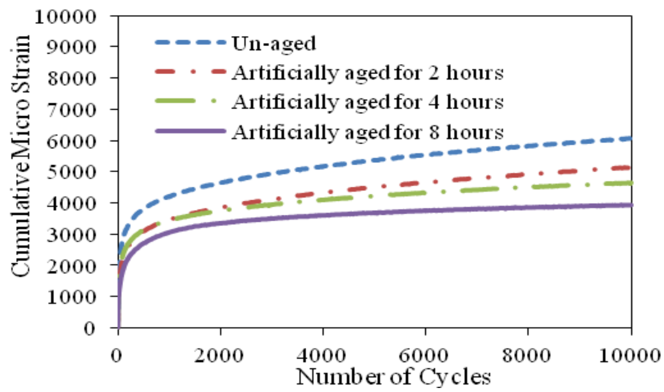

Figure 4. Cumulative micro strain of mixtures tested at 40°C.

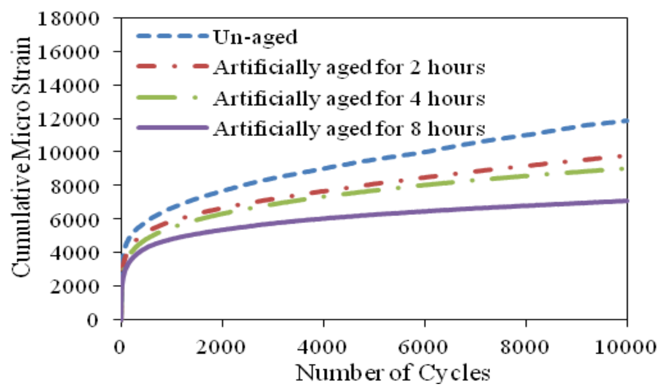

Figure 5. Cumulative micro strain of mixtures tested at 50°C.

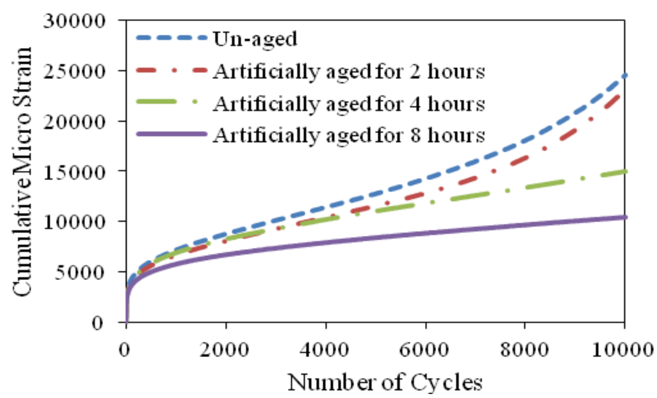

Figure 6. Cumulative micro strain of mixtures tested at 60°C.

3.2 Mathematical Model Evaluation

Superpave model was utilized to predict the accumulated permanent strain of mixtures plotted on a logarithmic scale at different aging stages. From the experimental results, coefficients for averages of 3 tested samples are calculated as shown in Table 6. Superpave model with new constant parameters was then used to postulate the estimated values. The predicted and measured values were then compared and the results are shown in Figure 7. The results in Table 6 indicate that the Superpave model can predict probable deformations of pavement with an acceptable accuracy at 40°C for all samples. However, its accuracy decreases with an increase in test temperature. For instance, the R^2 and RMSE of sample artificially aged for 2 hours and tested at 40°C are 98% and 0.9%, respectively, while the corresponding values change to approximately 60% and 13.6% at 60°C, respectively. On the contrary, the extension of aging duration enhances prediction accuracy. It can be seen from the R^2 and RMSE changes at 60°C. The R^2 of artificially aged samples for 2 hours is 60%, while the corresponding values increase to approximately 85% and 87% for samples artificially aged for 4 and 8 hours, respectively. The average R^2 of the samples artificially aged for 8 hours exhibit the highest value which indicates the highest prediction accuracy. Conversely, the average R^2 of the samples artificially aged for 2 hours exhibit the least values which indicate the least prediction accuracy. Such findings can be correlated to the lower mixtures temperature susceptibility due to higher rate of light oil fractions evaporation which resulted in stiffer mixtures. From Table 6 and Figures 4 to 6, it can be inferred that the Superpave model has the capability to accurately predict probable deformations of samples at the densification stage (primary phase) and steady-state zone (secondary phase). However, the model accuracy decreases when samples tend to progress to the tertiary stage, where air voids in the mixture reduced significantly. The measured and predicted values are also compared to verify the accuracy of the Superpave model results. From the results presented in Figure 7, the predicted values fit into the experimental observation with acceptable accuracy. This implies that the Superpave model is a good method to predict rutting formation. However, the Superpave model has a disadvantage of not being able to consider the aging level and predict rutting during tertiary creep accurately, therefore, it can only be used for a specific creep curve. To improve the accuracy of the model, overcome its precision at higher temperatures and develop the ability of combination of different aging conditions, modern pattern recognition techniques have been adapted to develop new models due to their ability to recognize trends in the data pattern as presented in Section 3.3.

Table 6. R^2%, RMSE%, and coefficient (S) for predicted models.

Aging Stage	Value	Temperature 40°C	50°C	60°C
Un-Aged	R^2 %	98	85	66
	RMSE %	1.1	3.7	10.3
	Coefficient (S)	0.1394	0.1392	0.1931
2H Aged	R^2 %	98	91	60
	RMSE %	0. 9	2.6	13.6
	Coefficient (S)	0.1437	0.1435	0.2090
4H Aged	R^2 %	98	92	85
	RMSE %	0.9	2.6	5.0
	Coefficient (S)	0.1530	0.1533	0.1874
8H Aged	R^2 %	94	97	87
	RMSE %	1.4	1.4	3.9
	Coefficient (S)	0.1396	0.1510	0.1654

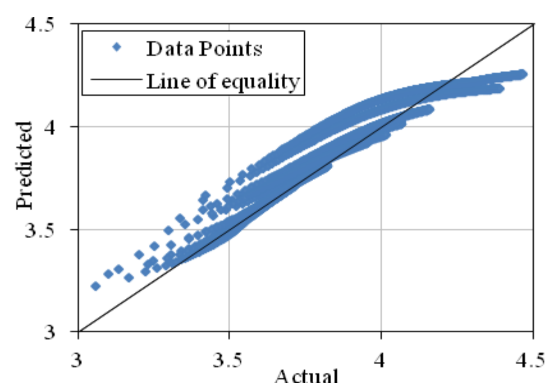

Figure 7. Predicted values using Superpave equation versus actual results (logarithmic scale).

3.3 Evaluation of Soft Computing Models

3.3.1 Evaluation of Artificial Neural Networks Model

Statistical parameters of ANN modeling for both training and testing sets are given in Table 7. The capability of proposed ANN to predict the cumulative strain with respect to training and testing sets is also demonstrated in Figures 8 and 9, respectively. The coefficient of determination in the case of both training and testing sets is 1.000. This finding demonstrates the POTENTIAL OF artificial neural network as a powerful tool to predict the cumulative strain from number of cycles, aging level, and temperatures. It can also be seen that the root mean square error (RMSE) in the case of the training and testing set is about 11. The equality of R^2 and RMSE resulted from ANN modeling for both training and testing sets affirm that the developed ANN has an excellent capability of generalization which means ANN is able to predict the cumulative strain accurately when new input parameters are provided.

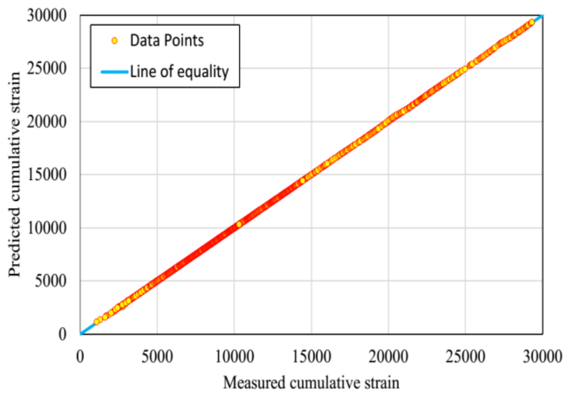

Figure 8. Performance of ANN for modeling of cumulative strain based on the training set.

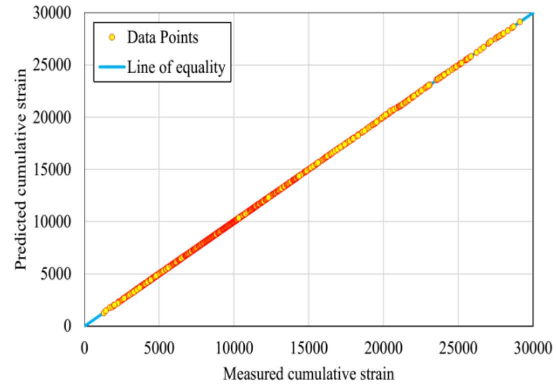

Figure 9. Performance of ANN for modeling of cumulative strain based on the testing set.

Table 7. Statistical parameters of ANN modeling.

Data set	Training set	Testing set	Overall
RMSE	10.83	10.81	10.82
R^2	1.000	1.000	1.000

3.3.2 Evaluation of Supporting Vector Machine

Statistical parameters of SVM regression for both training and testing sets are given in Table 8. The coefficient of determination R^2 in the case of the training set, testing set, and overall data is equal to 0.999 which is comparable with the results of modeling using artificial neural networks. The developed SVM has an acceptable generalization because the coefficients of determination for both training and testing sets are approximately the same. Figure 10 illustrates the capability of SVM for predicting cumulative strain based on the testing set. The results indicate that the SVM can also be used for modeling the probable deformation of mixtures in terms of the number of cycles, aging level, and temperatures with acceptable accuracy.

Table 8. Statistical parameters of SVM regression.

Data set	Training set	Testing set	Overall
RMSE	160.47	158.98	160.02
R^2	0.999	0.999	0.999

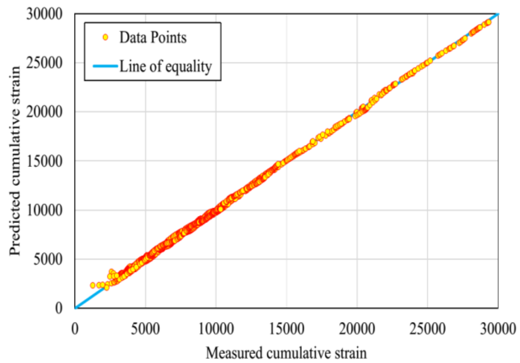

Figure 10. Performance of SVM for modeling of cumulative strain based on the testing set.

3.3.3 Comparison between Mathematical, Artificial Neural Networks and Supporting Vector Machine Models

From the results, the accuracies of both ANN and SMV methods to model the cumulative strains are higher compared to the accuracy obtained from the mathematical method. In addition, the accuracy of SVM modeling is lower in comparison with the ANN method. This is evident by comparing R^2 and RMSE in the case of the testing dataset. The RMSE and R^2 for ANN modeling are about 11 and 1.000, respectively, while the corresponding values for SVM modeling are 159 and 0.999, respectively. Moreover, the mathematical modeling exhibited only great potential to model one specific dynamic creep curve in certain aging levels and temperature which means under other conditioning circumstances (different aging levels and temperatures from experimental tests), the developed mathematical models cannot be employed. In contrast, ANN and SMV methods have the capability to generalize other conditioning circumstances and they can practically be used to predict the cumulative strain at different aging levels and test temperatures.

4. Conclusion

The effects of aging on asphalt mixture rutting behavior were quantified and modeled using Superpave model, Artificial Neural Network (ANN), and Supporting Vector Machine (SVM) techniques. Extending the aging duration decreases the cumulative strain, while escalating test temperature increases the corresponding value of all tested samples. Models were developed from the experimental outcomes obtained from the dynamic creep test. From the results, the Superpave model can predict probable deformations of samples with an acceptable accuracy level at 40°C, while its accuracy decreased as testing temperature elevated. The Superpave model accuracy decreased once samples tend to progress to the tertiary creep. The Superpave model exhibited another disadvantage, namely; it can only be used for a specific creep curve. On the contrary, ANN and SVM techniques exhibited the capability of considering all parameters including the aging level and test temperature concurrently to develop accurate models. The difference between the precision of all developed models' showed that the predicted results using ANN technique are in a better agreement with the experimental data compared to other methods. It was finally concluded that ANN with appropriately trained architecture can be the most accurate, effective, and promising tool to predict the rutting behavior of asphalt mixtures subjected to different conditions. It should be noted that the developed soft computing methods in this paper are valid in the case of the tested asphalt mixtures. With the development of such models, it is possible to predict permanent deformation of the asphalt mixture subjected to aging without the need for additional experiments.

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