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Artificial intelligence approach to predict the dynamic modulus of asphalt concrete mixtures

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Abstract: This paper develops an Artificial Neural Network (ANN) model based on 96 experimental data to forecast the dynamic modulus of asphalt concrete mixtures. The accuracy of the models was assessed using numerous performance indexes such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). In addition, this study applied the repeated K-Fold cross-validation technique with 10 folds on the training data set to make the simulation results more reliable and find a model with more general predictive power. According to the research findings, the ANN model accurately predicts the dynamic modulus |E*| of asphalt concrete mixtures. Furthermore, the ANN model could successfully predict the dynamic modulus |E*| of asphalt concrete mixtures with a remarkable R^2 = 0.989.

Keywords: Artificial neural network (ANN), artificial intelligence (AI), machine learning (ML), dynamic modulus, asphalt concrete mixtures

1. Introduction

Asphalt concrete mixtures are materials with many advantages, such as being easy to construct with high productivity, can be open to traffic immediately after construction, being good quality, uniform, easy to repair. However, asphalt concrete mixtures is a material that is sensitive to temperature and humidity, so in the operation process, under the effect of heavy loads, large vehicle traffic combined with environmental impacts such as high temperatures and humidity, asphalt pavement is easily degraded in quality leading to damage, rutting, permanent deformation, fatigue cracking.

Dynamic modulus of asphalt concrete mixtures (|E*|) is one of the essential input factors of asphalt mixture used to analyze pavement structure using the mechanistic-empirical method. Dynamic modulus, |E*|, has not only been increasingly acknowledged as a vital material property in mechanistic-empirical design and analysis [1], but also reflects the pavement structures induced by loading rate and temperature [2–4]. Based on experimental studies, the United States developed predictive models for |E*| and other factors such as volume of air voids (V_a), voids in mineral aggregate (VMA), effective binder content by volume (V_{beff}) for the analysis of flexible pavement structure using the mechanistic-empirical method. However, such predictive models were established under the specific conditions of the United States in certain projects. Therefore, they are only suitable with the specificities of materials, climate conditions of such projects. For that reason, to apply the predictive models |E*| in other countries such as Vietnam, it is required to adjust the coefficients in the predictive models according to the conditions of local materials. Various techniques for forecasting the dynamic modulus |E*| have therefore been presented, including regression analysis based on laboratory data [5–7], modification of an existing prediction equation in AASHTOWare [8], and Artificial Intelligence methods [3,9]. The most widely utilized comprehensive and scientific technique in laboratory measurements is tied to a mechanistic approach, namely the Mechanistic-Empirical Pavement Design Guide (MEPDG). However, the experimental approach may not always be achievable due to a lack of facilities or equipment.

Furthermore, some investigations have found that these models overemphasize the influence of temperature, and the mixture parameters or overpredict the dynamic modulus, such as Birgisson et al. [10], and Kim et al. [11]. On the other hand, the Hirsch model has been found to underestimate the dynamic modulus, as reported by Ceylan et al. [12]. These findings revealed that the theories for predicting the predicted dynamic modulus |E*| still need to be further investigated.

In the past few years, artificial intelligence has been one of the advanced techniques in the industrial 4.0 era that has been applied in many fields of technical science and natural science to solve real-life problems, initially showing outstanding effectiveness and benefits. These methods are also used to predict many essential pavement parameters in the transport sector. Le et al. [13] developed an alternative numerical tool using an artificial neural network (ANN) to predict SMA mixtures' Marshall Stability and Marshall Flow. Nguyen et al. [14] used an adaptive open neural inference system to predict the international roughness index IRI. Le et al. [15] developed three AI models, namely GAANFIS, PSOANFIS, and SVM, to predict the Marshall Parameters of Stone Matrix Asphalt. The ability and effectiveness of artificial intelligence techniques in predicting roadbed stability and traffic-related problems have also been evaluated and confirmed in many other studies [16–24]. The above studies show that it is feasible to apply artificial intelligence techniques to predict the dynamic modulus of asphalt concrete mixtures.

In this study, an ANN model is proposed to study and predict the dynamic modulus |E*| of asphalt concrete mixtures. A number of 576 dynamic modulus experimental tests were conducted to create a database of 96 examples based on the average values per 6. This data set is then used to build and evaluate the predictive capacity of the proposed ANN model. The model development process is divided into two phases, the training phase using 70% of the data and the validation phase using the remaining 30% of data. The criteria to evaluate the predictive performance of ANN used in this study include root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2).

2. Database construction

This study used 96 experimental data performed by the same group of authors, already published [15], to develop a predictive model of the dynamic modulus of asphalt concrete mixtures. The ANN model is built using four parameters denoted as Mix, Tech, Freq, and Temp. These are the factors that affect the dynamic modulus of asphalt concrete mixtures. Besides, the output parameter considered is the dynamic modulus denoted by |E*| (MPa). All data is scaled to the range [0,1] to reduce numerical errors during the simulation processing, as recommended by [25].

Considering the input parameters, the Mix is the asphalt concrete mixtures, representing two types of mixtures, namely Stone Mastic Asphalt (SMA) and Dense-graded asphalt concrete mixtures (DGA). Tech stands for mixing techniques, including warm mixing techniques and hot mixing techniques. Freq is the experimental frequency (Hz), covering six frequency values such as 0.1, 0.5, 1, 5, 10, and 25 (Hz). Finally, Temp is the experimental temperature (i.e., 10°C, 25°C, 45 °C, 60°C).

Figure 1 shows the distribution of the parameters used in this study, combined with the Pearson correlation coefficient between those parameters. In addition, Figure 1 also shows the correlation between input variables and between input variables and output variables. Based on the value of the correlation index (r_s), the correlation level can be divided into the following levels: r_s=0÷0,19 (very weak correlation), r_s=0,2÷0,39 (weak correlation), r_s=0,4÷0,59 (moderate correlation), r_s=0,6÷0,79 (strong correlation), r_s=0,8÷1,0 (very strong correlation) [26]. Therefore, based on the r_s value in Figure 1, it can be seen that the correlation between asphalt concrete mixtures (Mix), mixing techniques (Tech) and experimental frequency (Freq), and dynamic modulus |E*| is very weak. At the same time, there is only a correlation between experimental temperature (Temp) and dynamic modulus |E*| is strong. Through this initial analysis, it can be seen that four input parameters of the data set are considered independent variables. Consequently, in this study, all variables will be used to increase the accuracy and generality of the forecasting model.

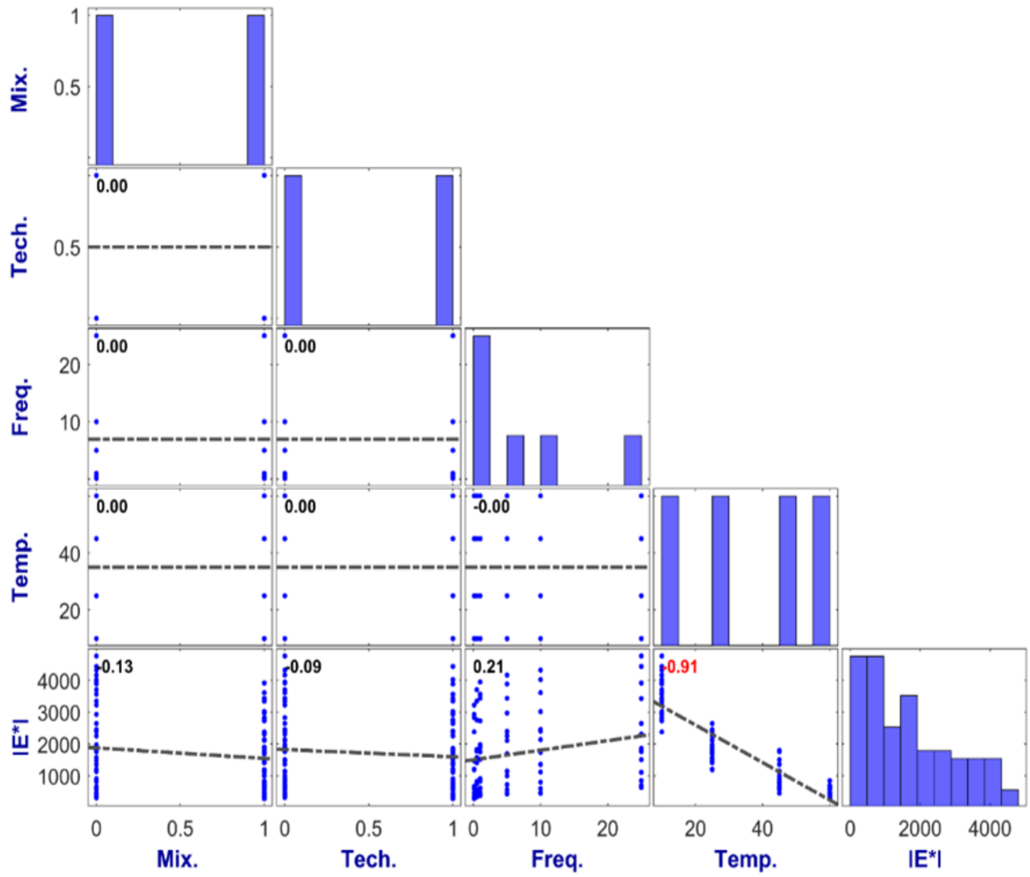

Fig. 1. The distribution chart and correlations between input and output parameters

3. Model Details

3.1. Artificial Neural Network (ANN)

Artificial Intelligence (AI) is a knowledge topic that focuses on creating computer systems that can solve issues by granting them cognitive abilities to do jobs that would typically need human intelligence. As a result, the primary goal of AI is to simulate human intellect using computer programming and technology. Machine learning (ML), on the other hand, is one of the disciplines of AI in which computer systems are programmed depending on data and input type. ML provides the capacity to solve many complex issues using data. Similarly, an artificial neural network (ANN) is a creative way of machine learning algorithms based on the idea of simulating the human brain [27]. The artificial neural network is a machine learning methodology that evolved and developed from the scheme of imitating the human brain. ANN can reconstruct several functions of human behavior, performed by a finite number of layers with different computing elements called neurons [28]. The input, hidden, and output layers make up the ANN structure. The input and output layers have a connection through one or many hidden layers. Prediction, pattern recognition, classification problem, and finding a relationship between complex featured variables are common use cases of ANN.

3.2. Repeated K-Fold cross-validation

Cross-validation (CV) is a technique commonly used in machine learning and artificial intelligence problems. CV is a solution that provides the ability to estimate or help to generalize the performance of a machine learning model against data for which the model is not known (learned) during the training phase. There are two main steps to perform CV, namely splitting the data into subsets (called folds), and alternating training and validation process between them. Splitting techniques typically have the following characteristics: (i) each fold is approximately the same size, (ii) the data can be randomly selected per fold or stratified, (iii) all folds used to train the model except one used for validation, and the validation fold must be rotated until all folds become one-time validation folds, and only one time. The fold (k) will be chosen as 5 or 10 to ensure the overall ability to evaluate the model's performance. In this study, the value k=10 was chosen. The validation data in the original dataset is separated into separate parts, and the training (including model training and validation) does not use that validation data. An illustration of the CV cross-validation technique is shown in Figure 2 with 10 CVs and three datasets, including training, validation, and verification.

The k-fold cross-validation procedure is a standard method for estimating the performance of a machine learning algorithm or configuration on a dataset. A single run of the k-fold cross-validation procedure may result in a noisy estimate of model performance. In addition, different splits of the data may result in very different results. Repeated k-fold cross-validation provides a way to improve the estimated performance of a machine learning model. This involves simply repeating the cross-validation procedure multiple times and reporting the mean result across all folds from all runs. This mean result is expected to be a more accurate estimate of the model's proper unknown underlying mean performance on the dataset, as calculated using the standard error.

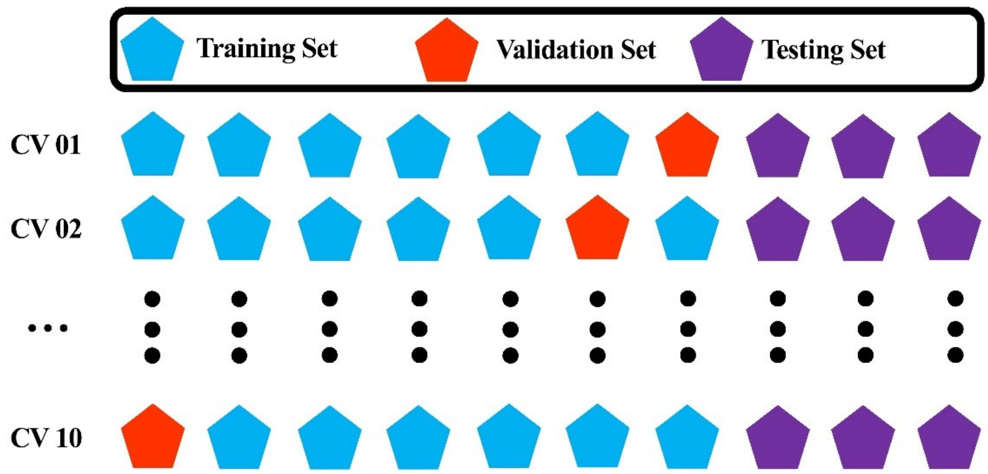

Fig. 2. Cross-validation technique with 10-fold used in this study

3.3. Performance assessment

The efficiency of the developed models is evaluated using various statistical indexes, namely, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The R^2 value ranges from [-∞, 1], the higher R^2 value (i.e., closer to 1) indicates a more successful model. On the contrary, the lower value of RMSE, MAE, MAPE indicates better performance of proposed AI models. The criteria are determined by the following equations (1), (2), (3), (4):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_0 - y_p)^2}{\sum_{i=1}^{N}(y_0 - \overline{y}_i)^2} \quad (1)$$

$$RMSE = \sqrt{\sum_{i=1}^{N}(y_0 - y_p)^2 / N} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_0 - y_p\right| \quad (3)$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{y_0 - y_p}{y_0} \quad (4)$$

where N is defined as the number of input data, $\bar{y}$ is the mean value of the outputs, and y_0 and y_p express the actual and modeled values, respectively.

4. Results & Discussion

The process of building the ANN model is performed in this section, using repeated K-Fold cross-validation to perform on a set of 96 data. This section displays typical ANN model prediction results after ten repeated cross-validation. The process consists of two phases: (i) the training phase, which is the process of training the model accompanied by cross-validation with ten folds; (ii) when the ANN tool achieves the optimal prediction performance on the training data set, the evaluation will be performed on the testing dataset. The training dataset (accounting for 70% of the samples) was divided into ten parts to conduct cross-validation, as recommended in [17]. This process is repeated ten times, and then the final prediction evaluation criteria will be averaged for each time. It is worth noticing that the testing dataset (which accounts for the remaining 30% of data) is only used to evaluate the model's predictive ability for unknown data. The ANN model prediction performance evaluation results for both data sets are shown in Figure 3. The utilized ANN architecture was 4-5-1 (using 5 neurons in a single hidden layer), sigmoid as activation function, and resilient back propagation training algorithm.

It can be noticed that the proposed ANN model with ten-fold cross-validation has outstanding predictive performance. Moreover, there is no overfitting phenomenon because the capacity of ANN in the training set is better than in the testing dataset. Moreover, this observation is valid for all 10 times repeated k-fold CV. It can be seen that for the training data set, the performance evaluation criteria vary within specific intervals but are relatively small. Precisely, RMSE fluctuates in the range of 100 - 150. The best run has the value RMSE=100, and the worst run is RMSE=150, corresponding to the third and eighth runs. The same statement is also verified by MAE, when the mean of MAE was 95, and the best simulation was at run 3 (MAE=76) and the worst at run 7 (MAE=114). With MAPE error, the values of MAPE range from 6 - 11, and the best simulation is at the second run (MAPE=6) and the worst at the eighth run (MAPE=11). R^2 evaluation criteria also made similar statements, when R^2 reached a value around 0.985, and the best was achieved with the second run (R^2 = 0.987), whereas the worst was in the eighth run (R^2 = 0.982). The trained ANN model has an excellent predictive ability with the training data set, which can be selected for testing on the testing dataset.

This section describes the typical prediction results for the ninth run because R^2 is the highest for both train and test sets, and the other errors are the smallest. Experimental value and predictive value by ANN for train and test set are shown in Fig 4, clearly demonstrating that the predicted value is close to the actual value. Only 1 or 2 values (values 6, 15, and 34 in the train set and 5.9 and 11 in the test set) are different, but this difference is insignificant.

Fig.5 shows the ANN model's distribution plot and cumulative distribution line of error for the training part, while Fig.4b shows them for the testing part. According to the comparison, the projected value is near the experimental value. As observed, 80% of the error is in the range of -200 MPa to 200 MPa, and 75% is within ± 100 MPa for both the train and test sets. For the training set, only two error samples are -250 MPa, and three error samples are 250 MPa. As for the test set, there is one error sample of -300 MPa, 6 sample errors greater than 250 MPa. Thus, the training set has five error samples, and the test set has seven samples.

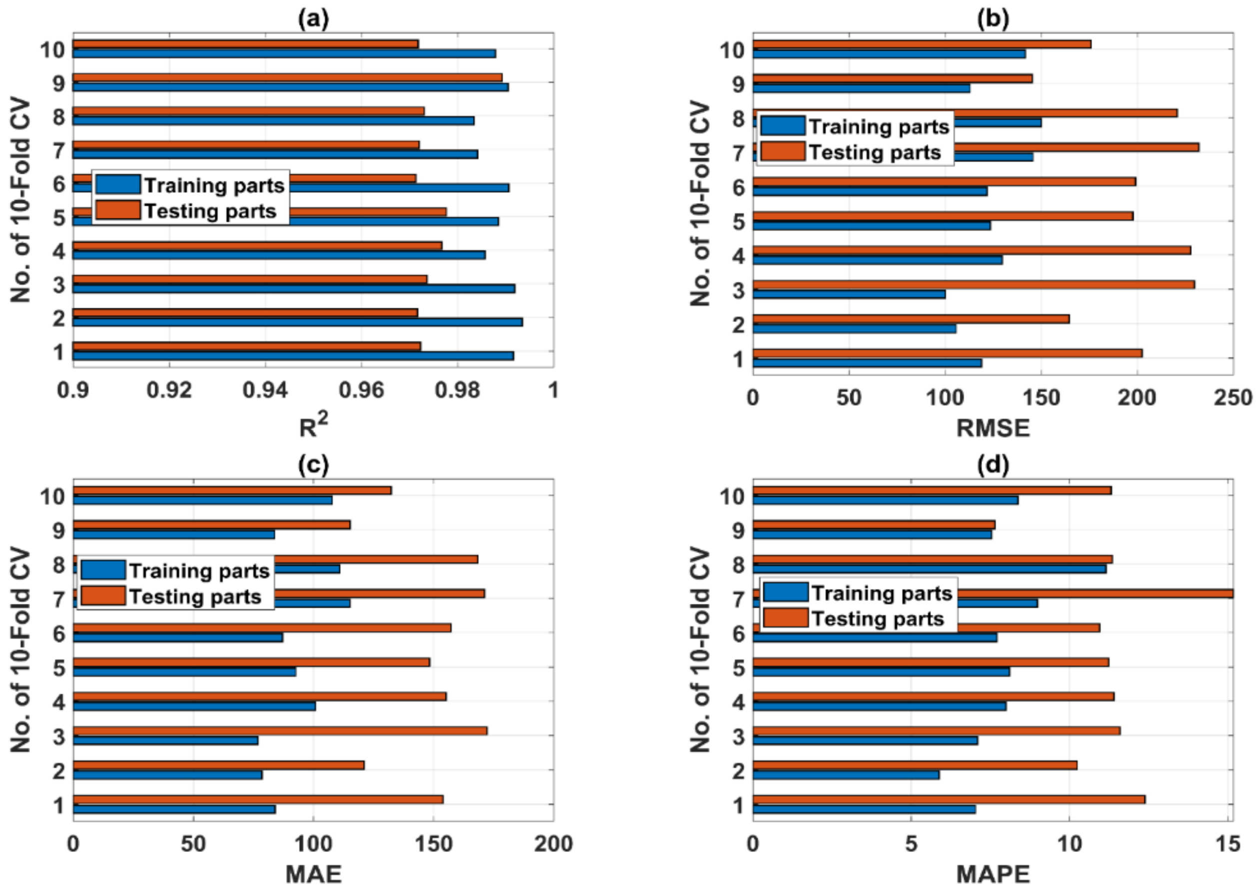

Fig. 3. Results of training and validation of ANN model after 10 - repeated 10 fold cross-validation based on different performance evaluation criteria: (a) R^2; (b) RMSE; (c) MAE; and (d) MAPE

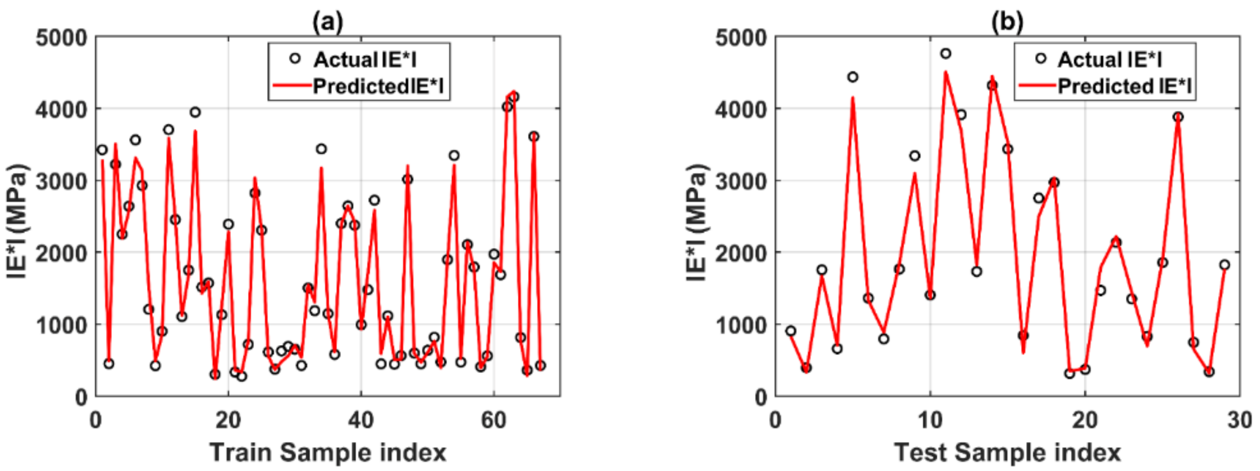

Fig. 4. Comparison of the performance of the ANN model with the actual values of R in the function of training dataset and testing dataset

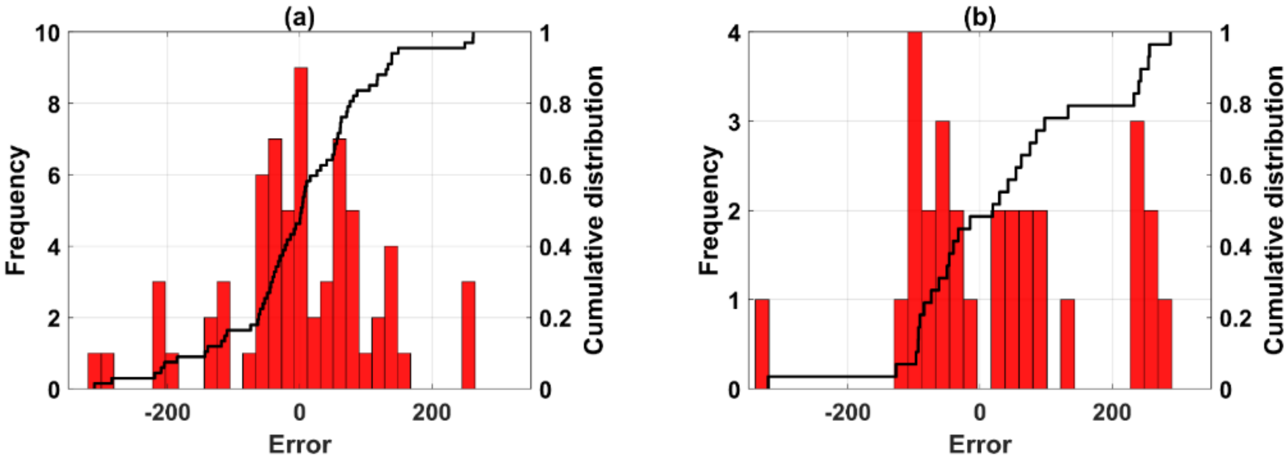

Fig. 5. Error and regression charts between experimental values and simulation values calculated by ANN are considered in this study (a) Training data; (b) Testing

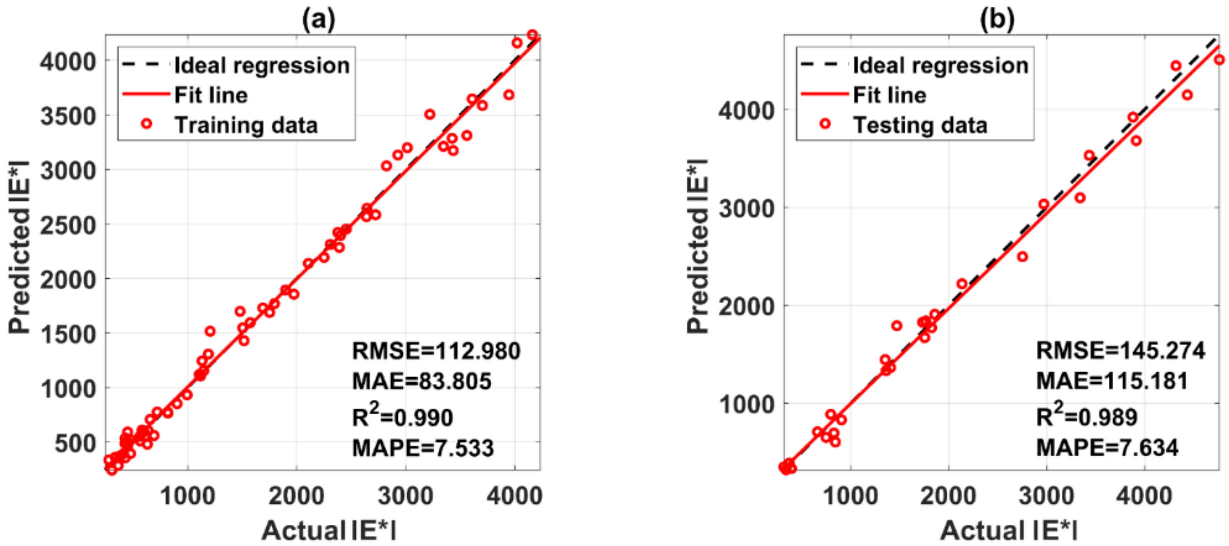

Fig. 6. Regression plot of the ANN model (a) Training; (b) Testing

In this section, the typical prediction results of the ANN model are presented through a regression graph, as shown in Figure 6. The regression model shows the correlation between predicted dynamic modulus |E*| (simulation) according to the ANN model and actual dynamic modulus |E*| (obtained from the experiment) for the training data set (Figure 6a) and the testing dataset (Figure 6b). The horizontal axis represents the results of the collected experiment, and the vertical axis represents the results predicted by the proposed model. The observation in Figure 6 shows that the values obtained from the proposed model for the training data set and the testing dataset are very close to the experimental results, which proves the accurate prediction ability of the model. Furthermore, the performance of the model is evaluated by the statistical criteria RMSE, MAE, MAPE, and R^2. In this case, the best predictor result for the training data set is RMSE = 112.980 MPa, MAE=83.805 MPa, MAPE=7.533 MPa, R^2=0.990 and testing dataset RMSE = 145.274 MPa, MAE=115.181 MPa, MAPE=7.634 MPa, R^2=0.989. The present study also achieves higher prediction performance than in [15] using a more complex algorithm, namely ANN with Teaching Learning Based Optimization (for the testing set, the authors achieve R^2 = 0.981, RMSE = 183.31, MAE = 141.54). The high values of R^2 combined with low error prove that the proposed ANN model can predict accurately and exhibits generalization performance in predicting dynamic modulus |E*| of asphalt concrete mixtures.

5. Conclusion

This study proposes an ANN model to predict asphalt concrete mixtures' dynamic modulus |E*|. For this purpose, 96 dynamic modulus experimental data tested in the laboratory are used to construct a model to predict the dynamic modulus of asphalt concrete mixtures. Four input parameters are used, including mixture type, technology, testing frequency, and temperature. Four criteria, RMSE, MAE, MAPE, and R^2 are used to evaluate the performance of the proposed ANN model. This study also applied the repeated K-Fold cross-validation technique with 10 folds on the training data set to make the simulation results more reliable and proposed a model with the most predictive ability. Research results show that the proposed model has good predictive performance and high accuracy in predicting the dynamic modulus |E*| of asphalt concrete mixtures, with performance evaluation criteria such as RMSE = 145.274 MPa, MAE=115.181 MPa, MAPE=7.634 MPa, R^2=0.989. Therefore, the ANN model developed in this study could be an effective tool for civil engineers to evaluate the performance of asphalt mixtures through dynamic modulus |E*|. In future studies, more recent techniques should be tested to assess the predictive performance compared with the current ANN model used in this study, such as Extreme Gradient Boosting or CatBoost.

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