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Advanced approaches to hot-mix asphalt dynamic modulus prediction

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Abstract

The dynamic modulus (|E*|) is one of the primary hot-mix asphalt (HMA) material property inputs at all three hierarchical levels in the new Mechanistic-empirical pavement design guide (MEPDG). The existing |E*| prediction models were developed mainly from regression analysis of an |E*| database obtained from laboratory testing over many years and, in general, lack the necessary accuracy for making reliable predictions. This paper describes the development of a simplified HMA |E*| prediction model employing artificial neural network (ANN) methodology. The intelligent |E*| prediction models were developed using the latest comprehensive |E*| database that is available to researchers (from National Cooperative Highway Research Program Report 547) containing 7400 data points from 346 HMA mixtures. The ANN model predictions were compared with the Hirsch |E*| prediction model, which has a logical structure and a relatively simple prediction model in terms of the number of input parameters needed with respect to the existing |E*| models. The ANN-based |E*| predictions showed significantly higher accuracy compared with the Hirsch model predictions. The sensitivity of input variables to the ANN model predictions were also examined and discussed.

Keywords

artificial neural network, asphalt, dynamic (|E*|) modulus, mechanistic-empirical pavement design guide, prediction model

Disciplines

Civil Engineering | Construction Engineering and Management

Comments

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Advanced Approaches to Hot-Mix Asphalt Dynamic Modulus Prediction

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Abstract: The dynamic modulus (|E*|) is one of the primary Hot-Mix Asphalt (HMA) material property inputs at all three hierarchical levels in the new Mechanistic Empirical Pavement Design Guide (MEPDG). The existing |E*| prediction models were mainly developed from regression analysis of |E*| database obtained from laboratory testing over many years and in general lack the necessary accuracy for making reliable predictions. This paper describes the development of a simplified HMA |E*| prediction model employing the Artificial Neural Networks (ANN) methodology. The intelligent |E*| prediction models were developed using the latest comprehensive |E*| database that is available to the researchers (from the NCHRP Report 547) containing 7,400 data points from 346 HMA mixtures. The ANN model predictions were compared with the Hirsch |E*| prediction model which a has logical structure and a relatively simple prediction model in terms of the number of input parameters needed, among the existing |E*| models. The ANN-based |E*| predictions showed significantly higher accuracy compared to the Hirsch model predictions. The sensitivity of input variables to ANN model predictions were also examined and discussed.

Key Words: Dynamic (|E*|) Modulus; asphalt; artificial neural network; prediction model; MEPDG.

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Introduction

The dynamic modulus (|E*|) is one of the asphalt mixture stiffness measures that determines the strains and displacements in flexible pavement structure as it is loaded or unloaded. The asphalt mixture stiffness can alternatively be characterized via the flexural stiffness, creep compliance, relaxation modulus and resilient modulus. One of the most significant advantages of using |E*| is that researchers have accumulated over the last 50 years a wealth of historic laboratory data for the test's input and output variables. The |E*| is one of the primary Hot-Mix Asphalt (HMA) material property inputs at all three hierarchical levels in the new Mechanistic Empirical Pavement Design Guide (MEPDG) (NCHRP, 2004) developed under National Cooperative Highway Research Program (NCHRP) 1-37 A (2004) for the American State Highway and Transportation Officials (AASHTO). It is also a promising candidate for the Simple Performance Test (SPT) recommended by the NCHRP 9-19 (Witczak et al. 2002) and 9-29 (Bonaquist et al. 2003).

Level 1 of the MEDPG requires direct measurement of |E*| via laboratory test such as the simple performance test. Level 2 applies the |E*| predictive model for estimating |E*| combined with laboratory measured binder stiffness or viscosity. The |E*| in Level 3 is estimated from the same |E*| predictive model in level 2 with typical binder and mixture properties suggested by the designer based on past experience and engineering judgment. The |E*| predictive model at level 2 and level 3 in current version (version 0.9) of MEPDG (NCHRP 2006a) is the |E*| predictive model (so called as the 1999 version of Witczak |E*| prediction model) developed by Witczak and his colleges in 1999 (Andrei et al. 1999). However, this Witczak |E*| prediction model uses the conventional viscosity (η) instead of the binder dynamic shear modulus ($|G_b*|$) value of the asphalt binder, which requires a middle step of conversion from $|G_b*|$ (that current Superpave Binder Performance Grading (PG) system uses) to η (Al-Khateeb et al. 2006). In addition, it is for the most part an empirical regression model and does not adequately utilize volumetric composition in its formulation (Christensen et al. 2003).

Recently, a new revised version of Witczak's |E*| predictive model has been developed to overcome a middle step of binder parameter conversion in the current version (Bari and Witczak 2006). In addition to the calibration with extended database, the new revised model includes the |Gb*| and the binder phase angle (δ) instead of the η and the frequency (f) parameter. This new revised version of Witczak's |E*| predictive model will include the future version (version 1.0) of MEPDG (NCHRP 2006b). However, this new revised model is still an empirical regression model and requires many inputs (eight input parameters), which makes dealing with this model laborious.

The Hirsch |E*| model for HMA was developed to serve as a tool for analyzing the effect of changes in air voids, voids in mineral aggregate (VMA) and other volumetric mix factors on the modulus of asphalt concrete and related mechanical properties (Christensen et al. 2003). Since this model is based on a law of material for composite material, its structure is rational and logical. It is also relatively simpler than the Witczak |E*| model in that it requires fewer constituent properties including $|G_b*|$, voids filled with asphalt (VFA) and VMA of the asphalt mixture. However, the Hirsch |E*| model shows poor accuracy for the expanded |E*| database containing modified asphalt mixtures because the original model was developed using the limited data of asphalt mixtures which primarily consisted of unmodified asphalt binders (Al-Khateeb et al. 2006; Bari and Witczak 2006).

The primary objective of this study is to develop an intelligent |E*| prediction model with significantly higher prediction accuracy compared to the existing |E*| models, which could also be easily incorporated into the MEPDG. Over the past two decades, Artificial Neural Networks (ANNs) have emerged as powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional numerical and statistical methods (TR Circular 1999).

Recently, researchers at Iowa State University (ISU) developed a novel approach for predicting HMA |E*| using the ANN methodology based on the input parameters of the Witczak |E*| model (Ceylan et al. 2007). In this paper, research efforts related to the development of a simple approach for predicting HMA |E*| using the ANN methodology based on the input parameters of the Hirsch |E*| model are documented. The comprehensive |E*| database containing 7,400 data records, which were used in the development of the revised Witczak |E*| model (Bari and Witczak 2006), were used in developing the ANN models. This paper describes the development of ANN-based |E*| prediction models, comparison of ANN model predictions with the Hirsch |E*| model predictions, and the sensitivity of input variables to ANN model predictions.

Hirsch Model for Dynamic modulus (|E*|) of asphalt mixtures

|E*| is the response of the material under dynamic loading determined in the linear elastic or viscoelastic range by dividing the loading stress amplitude by the peak-to-peak recoverable strain (Al-Khateeb et al. 2006).

The definition of |E*| comes from the complex modulus (E*) consisting of both a real and imaginary component as shown in Equation 1:

[1] $E^* = E_1 + iE_2$

In which, $i = \sqrt{-1}$, E_1 is the storage modulus part of complex modulus, and E_2 is the loss modulus part of complex modulus. The |E*| can be mathematically defined as the magnitude of complex modulus as shown in Equation 2:

[2] $|E^*| = \sqrt{E_1^2 + E_2^2}$

|E*| is also determined experimentally as the ratio of the applied stress amplitude to the strain response amplitude under a sinusoidal loading as shown in Equation 3:

[3] $|E^*| = \dfrac{\sigma_o}{\varepsilon_o}$

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Here, σ_0 is the average stress amplitude and ε_0 is the average recoverable strain. The |E*| of an asphalt mixture is strongly dependent upon temperature (T) and loading rate, defined either in terms of load time (t) or frequency (f). Using time-temperature superposition concepts represented by shift factors as shown in Equation 4, the combined effects of temperature and loading rate or time can be represented in the form of a master curve relating |E*| to a reduced time (t_r) by a sigmoidal function described in Equation 5:

$$[4]\quad a(T) = \frac{t}{t_r}$$

where a(T) is shift factor as a function of temperature, t is time of loading at desired temperature, t_r is the reduced time of loading at reference temperature, and T is the temperature of interest.

$$[5]\quad Log\left|E^*\right| = \delta + \frac{\alpha}{1 + e^{\beta + \gamma(\log t_r)}}$$

Here, δ is the minimum value of |E*|, $\alpha + \delta$ is the maximum value of |E*|, β and γ are the horizontal location of the transition zone and its slope, respectively. The function parameters δ and α will in general depend on the aggregate gradation and mixture volumetrics while the parameters β and γ will depend primarily on the characteristics of the asphalt binder (Schwartz, 2005). The values for δ, α, β, and γ and the a(T) at each temperature are all simultaneously determined from test data using nonlinear optimization techniques. The |E*| of an asphalt mixture in the MEPDG, at all levels of temperature and time rate of load, is determined from a master curve constructed at a reference temperature (NCHRP 2004).

Numerous |E*| predictive models have also been developed over the last 50 years for estimating |E*| using available asphalt binder and mixture data, particularly knowing that dynamic modulus measurements at extreme conditions of temperatures and loading frequencies are hard to obtain in the laboratory. Among these models, the Witczak |E*| model developed by Witczak and his colleges (Witczak and Fonseca 1996; Andrei, et al. 1999; Bari and Witczak 2006) and the Hirsch |E*| model proposed by Christensen et al. (2003) seem to have reasonable capability for predicting |E*| of an asphalt mixture (Al-Khateeb et al. 2006).

Witczak and his associates (Witczak and Fonseca 1996; Andrei et al. 1999; Bari and Witczak 2006) have developed and modified a predictive equation for estimating |E*| of asphalt concrete as a function of mix design inputs and asphalt binder properties using a large database of thousands of dynamic modulus test data points. More detailed descriptions and research efforts related to the development of the Witczak |E*| model were summarized by Bari and Witczak (2006).

Christensen et al. (2003) proposed a modified Hirsch model for predicting |E*| of asphalt concrete based on the law of mixtures. The original Hirsch model as shown in Fig. 1 and Equation 6 was developed by T. J. Hirsch to calculate the modulus of elasticity of cement concrete or mortar in terms of one empirical constant, the aggregate modulus and cement mastic modulus, and mix proportions (Hirsch, 1961). Hirsch assumed that the response of the constituent materials (cement matrix, aggregate, and the composite concrete) behaved in a linear elastic manner.

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[6] $$\frac{1}{E_C} = \frac{v_{1S}}{E_1} + \frac{v_{2S}}{E_2} + \frac{(v_{1P} + v_{2P})^2}{(v_{1P}E_1 + v_{2P}E_2)}$$

where, E refers to the modulus, or some other material property, ν_{1s} and ν_{2s} refer to the volume fractions of phases 1 and 2, respectively, in series arrangement, ν_{1p} and ν_{2p} refer to the volume fractions of phases 1 and 2, respectively, in parallel arrangement, the subscript *c* refers to the composite, and the subscript 1 and 2 refer to different phases present in the composite.

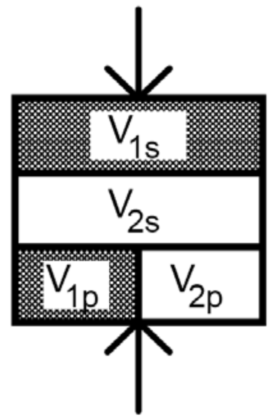

Fig. 1. Schematic representation of composite model for Hirsch arrangement of phases (Christensen et al. 2003).

Christensen et al. (2003) modified the original Hirsch model (Hirsch, 1961) to a relatively simple version for estimating the complex modulus and phase angle of asphalt concrete under shear and compression. They presented four alternative versions of a modified Hirsch model with different formulations as shown in Fig. 2: 1) series formulation; 2) parallel formulation; 3) dispersed formulation; and 4) alternate formulation. Their refinement and analysis showed that the first three versions of the Hirsch model did not provide good accuracy, but the fourth formulation (the alternate one), which is a generalization of parallel and series formulation, provided consistently better accuracy on their data. It was also found in their study that this version of the Hirsch model produced the best results and had the advantage over the other versions of the simplicity and the similarity to the original formulation of the Hirsch model (Al-Khateeb et al. 2006).

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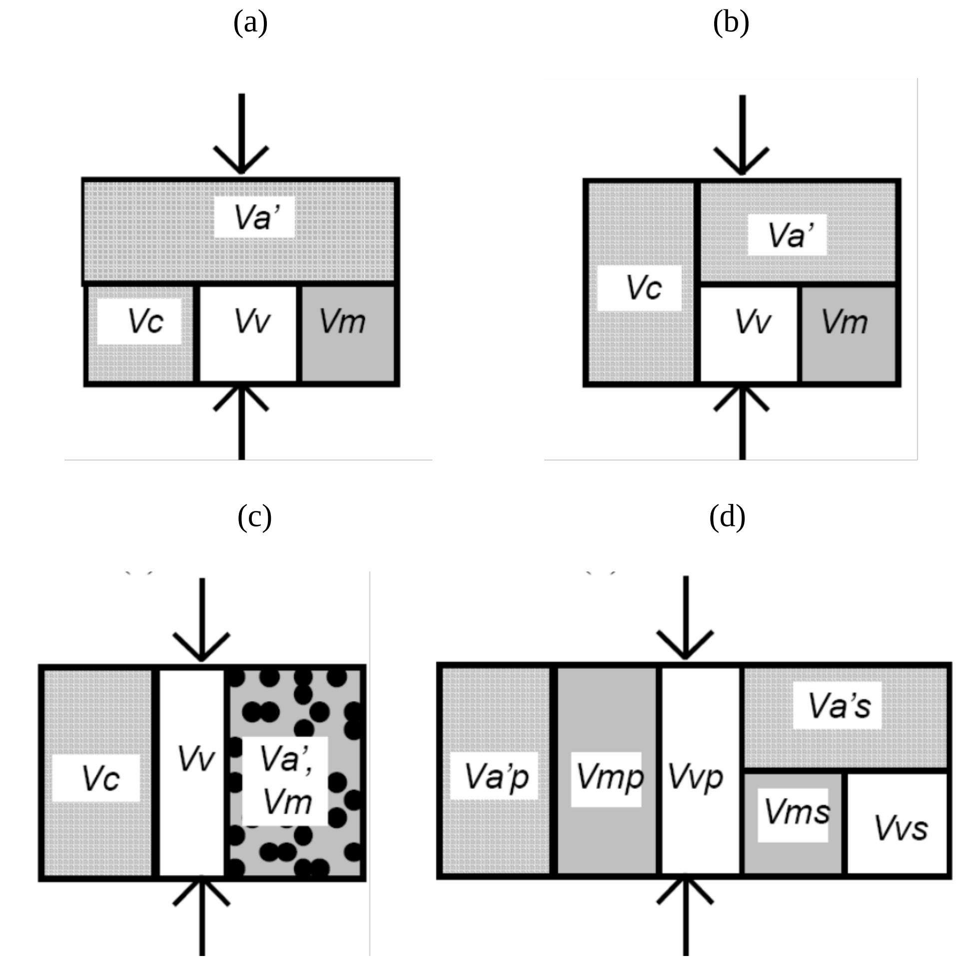

Fig. 2. Schematic representation of four alternate versions of modified Hirsch model (Christensen et al. 2003): (a) series version, (b) parallel version, (c) dispersed version, and (d) alternate version. $V_{a'}$, aggregate volume exclusive of the contact volume; $V_{a'p}$, aggregate volume exclusive of the contact volume in the parallel phase; $V_{a's}$, aggregate volume exclusive of the contact volume in the series phase; V_c, aggregate contact volume; V_m, mastic volume; V_{mp}, mastic volume in the parallel phase; V_{ms}, mastic volume in the series phase; V_v, air void volume; V_{vp}, air void volume in the parallel phase; V_{vs}, air void volume in the series phase.

What was common in the first three formulations presented in Christensen et al. (2003) is the use of what is called the aggregate contact volume (V_c) and the use of the asphalt mastic (asphalt binder + mineral filler) phase instead of the asphalt binder phase alone. The fourth formulation of the Hirsch model was further simplified by treating asphalt concrete as a three-phase system of aggregate, asphalt binder, and air voids (Equation 7). The use of what is called the contact factor (P_c) as described in Equation 8 was also introduced to represent the proportion of parallel to total phase volume.

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[7] $$E_C = p_c(V_a E_a + V_b E_b) + (1-P_C)\left[\frac{V_a}{E_a} + \frac{(V_b+V_V)^2}{V_b E_b}\right]^{-1}$$

where E_a represents the aggregate modulus, E_b represents the binder modulus, V_a represents the aggregate volume, V_b represents the effective binder volume, V_v represent is air volume and P_c represents the contact factor.

[8] $$P_C = \frac{(P_0 + \frac{VFA \times E_b}{VMA})^{P_1}}{P_2 + (\frac{VFA \times E_b}{VMA})^{P_1}}$$

where VMA is voids in the mineral aggregate, VFA is represents the voids filled with asphalt, E_b represents the binder modulus and P_0, P_1 and P_2 are empirically determined constants.

Using 206 data points obtained from 18 different HMA mixes originated from Federal Highway Administration's (FHWA's) Accelerated Loading Facility (ALF) project, the MnROAD Project, and the WesTrack Project, the refinement of Equations 7 and 8 were performed with a non-linear least squares method. Equation 9 (Christensen et al. 2003) shows the final equation of Hirsch model after refinement, which is the most effective version in different model formulations.

One of the main conclusions of their study was that the most effective version of the Hirsch |E*| model as shown in Equation 9 is relatively simpler than the Witczak model in that it requires fewer constituent properties inducing $|G_b^*|$, voids filled with asphalt (VFA) and voids in mineral aggregate (VMA) of the mixture. However, Bari and Witczak (2006) reported that the Hirsh |E*| model couldn't provide good prediction (R^2 = 0.61 in logarithmic scale and R^2 = 0.23 in arithmetic scale) when applied to a more expanded database used for the most recent revised version of the Witczak |E*| model in 2006, which contained 7,400 data points obtained from 346 different HMA mixes.

[9] $$|E^*|_{\text{mix}} = P_c\left\{4\,200\,000(1-\text{VMA}/100) + 3|G^*|_{\text{binder}}\left[\frac{(\text{VFA})(\text{VMA})}{10\,000}\right]\right\} + (1-P_c)\left(\frac{1-\text{VMA}/100}{4\,200\,000} + \frac{\text{VMA}}{3\text{VFA}|G^*|_{\text{binder}}}\right)^{-1}$$

Using the database from FHWA's Accelerated Loading Facility (ALF) pavement mixtures, Al-Khateeb et. al. (2006) modified the Hirsch |E*| model and proposed a simplistic |E*| model requiring only two parameters ($|G_b^*|$ and VMA). This simplified Hirsch |E*| model provided good predictions for mixtures taken from the FHWA's ALF pavement with a standard error within the acceptable range.

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Neural Networks Approach to |E*| Prediction

Literature review (Dougherty 1995; TR Circular 1999; Adeli 2001) suggests that ANNs and other soft computing techniques like fuzzy mathematical programming and evolutionary computing (including genetic algorithms) are increasingly used instead of the traditional methods in civil and transportation applications (Flintsch 2003). The recent adoption and use of ANN modeling techniques in the MEPDG (NCHRP 2004) has especially placed the emphasis on the successful use of neural nets in geomechanical and pavement systems. A current Transportation Research Board subcommittee AFS50(1) [formerly A2K05(1)] has been focused on "Applications of Nontraditional Computing Tools Including Neural Networks" with the primary mission to provide practitioners a better understanding on and at the same time foster the use of the ANNs and other nontraditional computational intelligence techniques in pavement engineering applications. In this study, the ANN methodology was used to develop robust |E*| prediction models based on the latest comprehensive |E*| database.

The basic element in the ANN is a processing element (artificial neurons). An artificial neuron receives information (signal) from other neurons, processes it, and then relays the filtered signal to the other neurons (Tsoukalas and Uhrig 1997). The receiving end of the neuron has incoming signals X_1, X_2 , . . ., and X_n. Each of them is assigned a weight, which is given based on experience and which may change during the training process. The summation of all the weighted signal amounts yields the combined input quantity I_k. The combined input quantity I_k is then sent to a pre-selected transfer function (sometimes called an activation function) T, and a filtered output Y_k is generated in the outgoing end of the artificial neuron k through the mapping of the transfer function. The process can be written as the following Equations 10 and 11:

$$[10]\quad I_K = \sum_{i=1}^{n} w_{ik} x_i$$

$$[11]\quad Y_K = T(I)$$

There are several types of transfer functions that can be used, including sigmoid, threshold, and Gaussian functions. The transfer function most often used is the sigmoid function because of its differentiability. The sigmoid function can be represented by the following Equation 12:

$$[12]\quad T(I) = \frac{1}{1 + \exp(-\varphi I)}$$

where φ = positive scaling constant, which controls the steepness between the two asymptotic values 0 and 1 (Tsoukalas and Uhrig 1997).

The ANN performs two major functions: learning (training) and testing. This study used the backpropagation learning algorithm for the ANN, which is a supervised learning algorithm in which the network is trained on a set of input–output pairs. Backpropagation ANNs are very powerful and versatile networks that can be taught mapping from one data space to another using a representative set of patterns/examples to be learned. The term "backpropagation network"

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actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. The learning process performed by this algorithm is called "backpropagation learning" which is mainly an "error minimization technique" (Haykin 1999).

In the development of backpropagation ANN models, the connection weights and node biases are initially selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct answers are then propagated backwards through the network and the connection weights and node biases are individually adjusted to reduce the error. After many examples (training patterns) are propagated through the network many times, the mapping function is learned with some specified error tolerance. This is called supervised learning because the network has adjusted functional mapping using the correct answers. The network is considered to be well trained when the error reaches a minimum or an allowable limit. The network performance is verified by presenting unknown testing datasets to the ANN after training is completed. Backpropagation ANNs excel at data modeling with their superior function approximation (Haykin 1999; Meier and Tutumluer 1998).

For this specific problem, a range of (-0.2, +0.2) was used for random initialization of all synaptic weight vectors in the network with a bias. For this problem, the *sigmoidal* function was chosen as the nonlinear activation function at the output end of all hidden neurons. Since, the final outputs (layer moduli) are real values rather than binary outputs, a *linear combiner* model was used for neurons in the output layer, thus omitting the nonlinear activation function. A smooth learning curve was achieved with a learning-rate parameter of 0.5 and a momentum of 0.5.

Preparation of ANN Database

Input variables for the |E*| ANN prediction model were retrieved from the NCHRP Report 567 CD-ROM (CRP-CD - 46) "Simple Performance Tests: Summary of Recommended Methods and Database." (Witczak, 2005).The CRP-CD-46 included as an appendix in the NCHRP report 567 contains not only |E*| new database (ASU and UMD database) but also all data and information collected and used during the NCHRP 9-19 study. The four input variables of the Hirsch |E*| predictive equations (see Equation 9) were used in the ANN model (ANN Hirsch). The one output variable was the |E*| in the ANN model. A total of 7,400 data records (which were also used in developing the new and revised Witczak |E*| model) was used in developing the ANN model. Table 1 shows the description and ranges of values for all input and output variables used in the ANN models.

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Table 1. Definitions and Ranges of Values for Input and Output Variables used in ANN Training.

Variable		Range Min	Max	Mean	S.D.
Mixture volumetric	VMA, %	10.3	34.6	17.5	3.7
	VFA, %	32.8	99.4	61.8	10.6
Binder	$\|G_b^*\|$, kPa	0.1	50,930.6	6,867.3	9,695.1
Contact factor	P_c	0	0.6	0.2	0.2
Dynamic modulus	$\|E^*\|$, GPa	0.1	59.6	9.0	10.1

The data were divided randomly into two different subsets: the training data subset containing 6,900 data points and the testing data subset which consisted of 500 data points. Both datasets were normalized within the range of -2 to 2 for input values and the range of 0.1 to 0.9 for output values to satisfy the transfer function (sigmoid) range and to prevent network saturation, which could impede the network's performance. The training data subset was used to train the backpropagation ANN |E*| prediction model and the testing data subset was used to examine the statistical accuracy of the developed ANN model. The trained ANN models were also finally evaluated using all the 7,400 data points to obtain the overall predictive accuracy and compare it with the existing |E*| predictive models.

Development of ANN |E*| prediction model

A typical four-layered, i.e., one input- two hidden–one output layer, feed forward error-back propagation ANN architecture, as shown in Fig. 3, was used in this study. To ensure efficient convergence and the desired performance of the trained network, several parameters were incorporated in the training phase. These parameters included the training rate, the momentum term, and the number of learning cycles (epochs).

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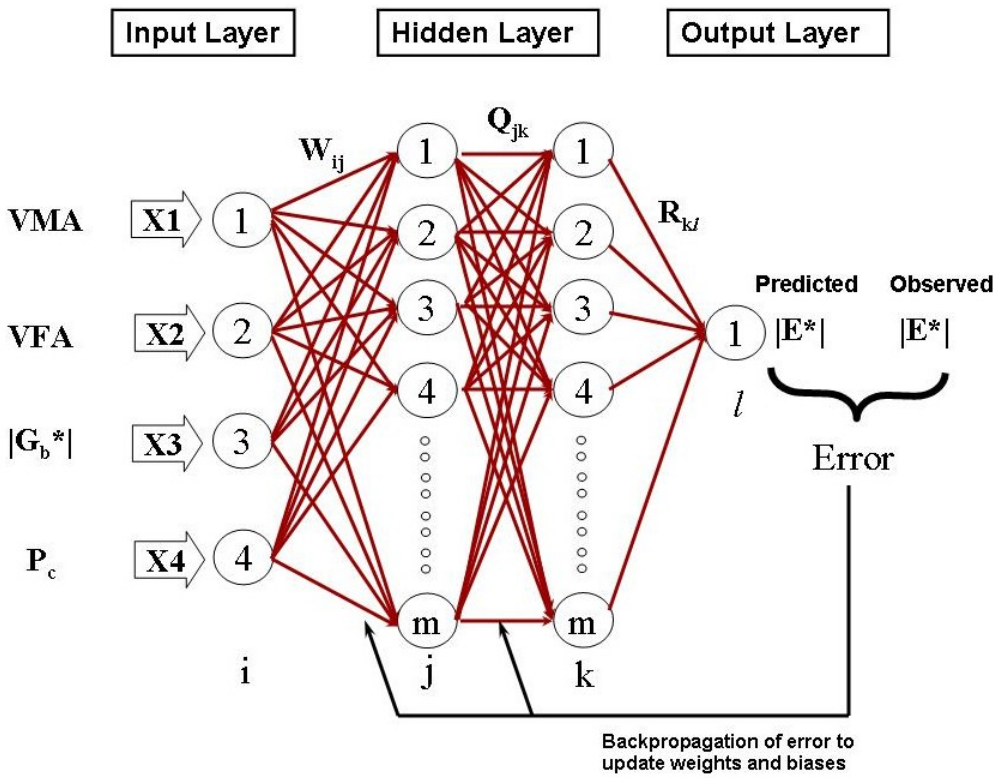

Fig. 3. Pictorial representation of four-layered neural network architecture used in this study.

The training rate is a factor that proportions the amount of adjustment applied each time the weight is updated. A small training rate might result in slower convergence and dropping into the local minima conditions in the weight-error space. A large training rate often causes the convergence behavior of the network to oscillate and possibly never converge (Owusu-Aabio 1998). The use of a momentum term could carry the weight change process through one or more local minima and get it into global minima. The training rate and the momentum coefficient used in the study were 0.4 and 0.6, respectively.

The ANN Hirsch |E*| prediction model has four input parameters including two mixture volumetric variables (VMA, VFA), one asphalt binder rheology property variable (|G_b*|) and one contact factor (P_c). The ANN model has |E*| as one output neuron. Several network architectures with two hidden layers were examined to determine the optimum number of hidden layer nodes through a parametric study. Overall, the training and testing mean squared errors (MSEs) decreased as the networks grew in size with increasing number of neurons in the hidden layers. The error levels for both the training and testing sets matched closely when the number of hidden nodes approached 40 as in the case of 4-40-40-1 architecture (4 input, 40 and 40 hidden, and 1 output neurons, respectively). Figure 4 shows the training and testing MSE progress curves for the 4-40-40-1 network for 10,000 learning cycles or training epochs. The 4-40-40-1 architecture was chosen as the best architecture for the ANN Hirsch model based on its lowest training and testing MSEs in the order of 2×10^{-3}. Both the training and testing curves for the output are in the same order of magnitude thus depicting proper training. The almost constant MSEs obtained for

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the last 6,000 epochs (Fig.4) also provided a good indication of adequate training for this network.

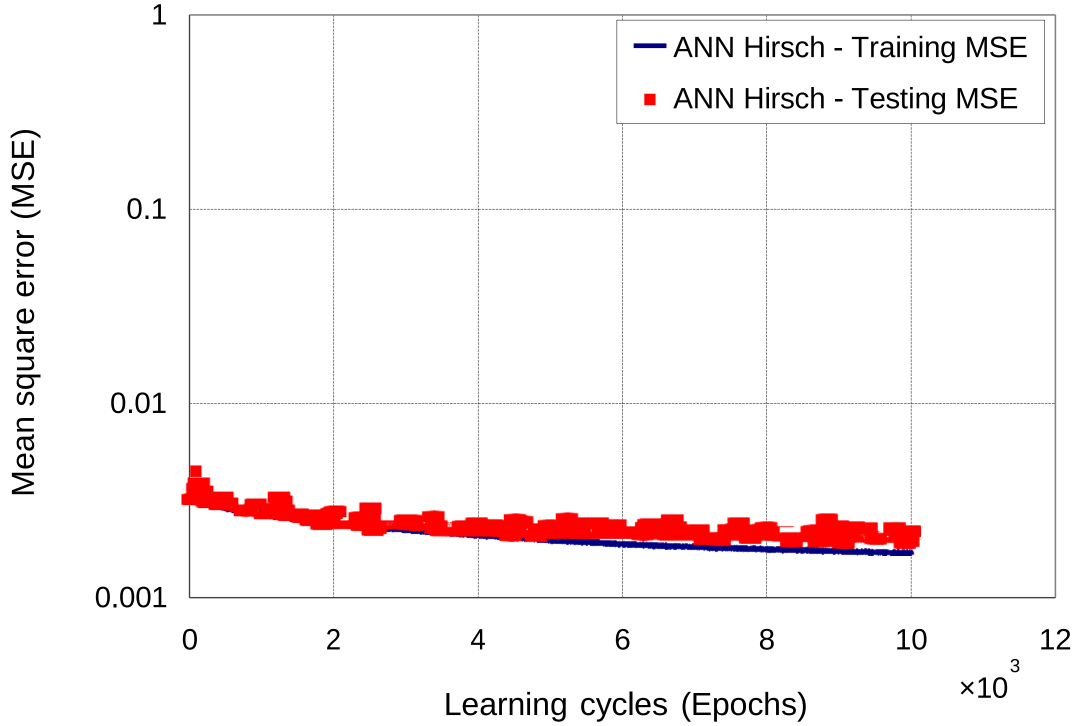

Fig. 4. Training and testing progresses of the ANN Hirsch model.

Results and Discussion

Goodness of Fit

The "goodness-of-fit" statistics for the ANN model predictions in arithmetic scale were performed using statistical parameters such as the correlation coefficient (R^2), the standard error of predicted values divided by the standard deviation of measured values (S_e/S_y), and the absolute average error (AAE). The R^2 is a measure of correlation between the predicted and the measured values and therefore, determines accuracy of the fitting model (higher R^2 equates to higher accuracy). The S_e/S_y and the AAE indicates the relative improvement in accuracy and thus a smaller value is indicative of better accuracy. A set of criteria in Table 2 originally developed by Pellinen (2001) were also adopted in this evaluation.

Reference to this paper should be made as follows: Ceylan, H., Gopalakrishnan, K., and Kim, S. (2008). "*Advanced Approaches to Hot-Mix Asphalt Dynamic Modulus Prediction*," Canadian Journal of Civil Engineering, Vol. 35, No. 7, pp. 699-707, doi: 10.1139/L08-016. Posted with permission.

Table 2. Statistical criteria for correlation between the observed and the predicted (Pellinen 2001).

Criteria	R^2	S_e/S_y
Excellent	≥ 0.90	≥ 0.35
Good	0.79 - 0.89	0.36 - 0.55
Fair	0.40 - 0.69	0.56 - 0.75
Poor	0.20 - 0.39	0.76 - 0.90
Very Poor	≤ 0.19	≥ 0.90

The results of statistical analysis are presented in Figs. 5 and 6 for the 500 testing data points and the 7,400 testing data points, respectively. As mentioned previously, the 500 test vectors form an independent dataset which was not used in training the ANN and it was used to test the accuracy of the trained ANN. The 7,400 datasets which form the entire |E*| database was used to obtain the overall ANN prediction accuracy statistics and compare with those of Hirsch |E*| model. Clearly, the ANN model predictions show "Good" statistics compared to Hirsch model predictions which show "Poor" accuracy. Especially, the AAE obtained using ANN is almost half that of Hirsch model. It is also noticed that the Hirsch predictions are more scattered below the line of equality (45 degree line) with increasing |E*| values. Especially, the Hirsch |E*| model seems to under-predict the actual measurement. In terms of performance, this lack of good prediction accuracy may translate into the risk of premature failure of the asphalt layer in rutting or fatigue. However, ANN model predictions are closely scattered around the line of equality without bias and therefore there is a higher chance of preventing premature distress failure.

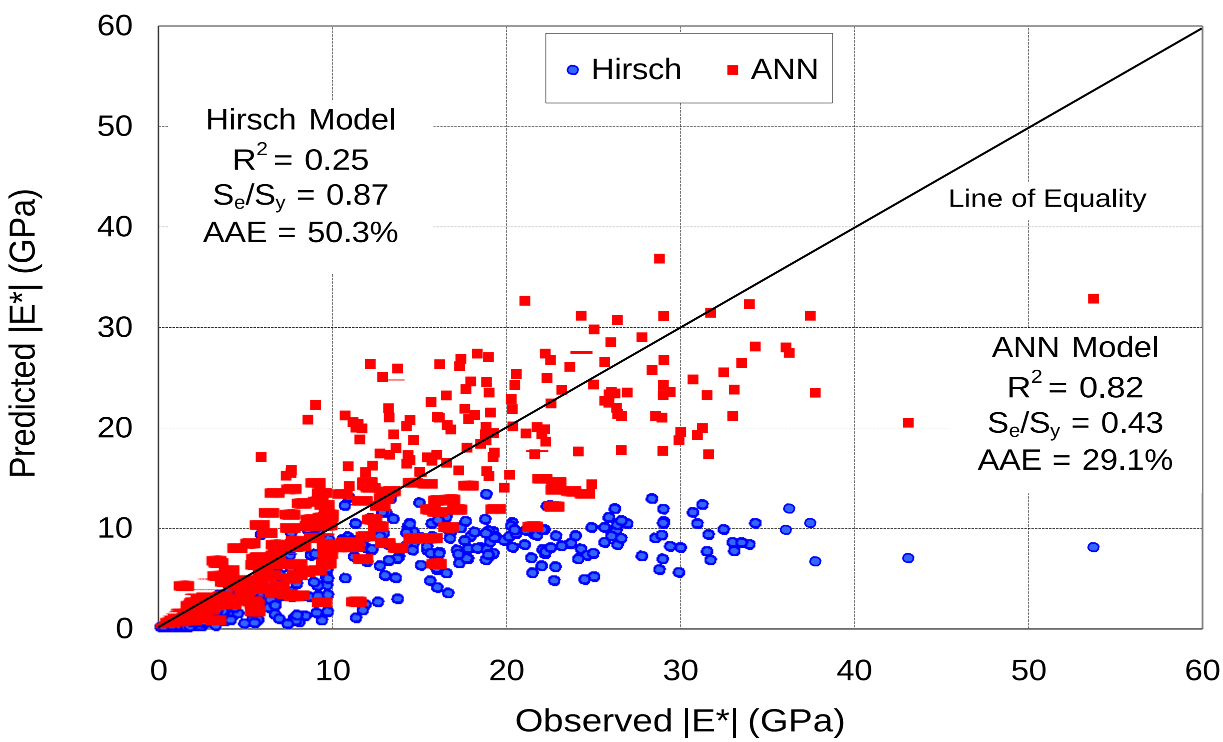

Fig. 5. Predicted versus observed |E*| using 500 testing data.

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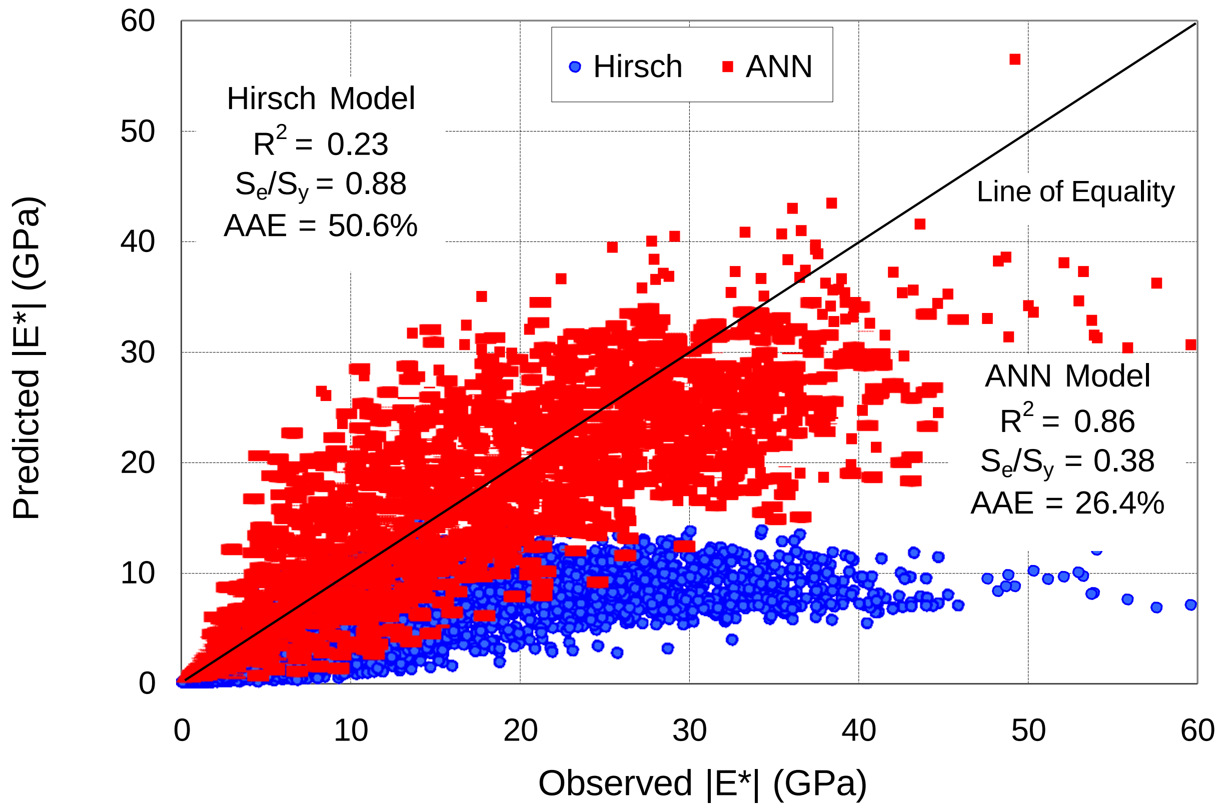

Fig. 6. Predicted versus observed |E*| using 7400 testing data.

Sensitivity Analysis of Input Variables in ANN Models

The sensitivity of ANN model predictions to the system variables was examined by examining the effect of different combinations of input parameters on |E*| prediction. Even though the 4-40-40-1 architecture was identified as the best architecture for the ANN Hirsch model, the 4-30-30-1 architecture was used to reduce the computation time.

The sensitivity analysis was generally conducted by changing one parameter value while keeping the other parameter values constant. Tables 3 and 4 display ANN models with different input variable combinations and the goodness-of-fit statistics corresponding to each ANN model for the 500 testing data points and the 7,400 testing data points, respectively.

The rational influence of the asphalt binder rheology property ($|G_b^*|$) to ANN model predictions can be observed from the goodness-of-fit statistics results of ANN H 1.1., ANN H 1.2. and ANN H. 2.1. model in Tables 3 and 4. The goodness-of-fit statistics (R^2 = 0.68 to 0.69) of the ANN H. 1.1. model using only $|G_b^*|$ input is close to the ANN Hirsch model (R^2 = 0.77 to 0.83). Even though the ANN H. 1.2. model doesn't include $|G_b^*|$, it still contains the effect of the asphalt binder rheology property with volumetric properties since P_c is the function of VMA, VFA and $|G_b^*|$ (Equation 9). Thus, the ANN H. 1.2. model shows "good" goodness-of-fit statistics (R^2 = 0.80). However, the exclusion of $|G_b^*|$ and P_c in ANN H. 2.1. model shows "Very poor" goodness-of-fit statistics (R^2 = 0). The observations from three ANN models indicate that the asphalt binder rheology property is the most sensitive variable in the ANN models.

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The effect of asphalt volumetric properties (VMA and VFA) on |E*| predictions can be observed from the goodness-of-fit statistics results of ANN H. 2.1., ANN H. 2.2., and ANN H. 2.3. model in Tables 3 and 4. Even though the ANN H. 2.1. model using only volumetric properties input (VMA and VFA) shows "Very poor" goodness-of-fit statistics (R^2 = 0), the exclusion of VFA in ANN H. 2.2. or VMA in ANN H. 2.3. model can influence the reduced accuracy (R^2 = 0.73 to 0.74) in comparison to the ANN Hirsch model (R^2 = 0.77 to 0.83). This results indicates that the ANN Hirsh models can capture the influence of non -asphalt binder property inputs (volumetric properties) on |E*| prediction.

The effect of the contact factor (Pc) was examined from the ANN H.3.1. and ANN H. 3.2.model in Table 3 and 4. The inclusion of P_c only in ANN H.3.1. can provide "fair" accuracy to |E*| prediction since P_c is a function of VMA, VFA and $|G_b^*|$. It is interesting that the exclusion of P_c in ANN H. 3.2. as shown in Fig. 7. can provide better accuracy (R^2 = 0.85) compared to the ANN Hirsch model (R^2 = 0.77 to 0.83). These results suggest that the ANN model can provide a "good" prediction of |E*| using only three parameters; $|G_b^*|$, VMA and VFA.

Table 3. Sensitivity analysis results for ANN models using 500 test data.

E* Predictive Models	Input parameter Property	Parameter	Goodness-of-fit in Arithmetic Scale R^2	Se/Sy	AAE (%)
Hirsch	Asphalt Binder, Volumetric, Contact Factor	VMA, VFA, $\lvert G_b^*\rvert$, P_c	0.25	0.87	50.3
ANN Hirsch (4-30-30-1)	Asphalt Binder, Volumetric, Contact Factor	VMA, VFA, $\lvert G_b^*\rvert$, P_c	0.77	0.48	31.5
ANN H. 1. 1. (1-30-30-1)	Asphalt binder	$\lvert G_b^*\rvert$	0.69	0.56	46.4
ANN H. 1. 2. (3-30-30-1)	Without asphalt binder	VMA, VFA, P_c	0.80	0.45	32.0
ANN H. 2. 1. (2-30-30-1)	Volumetric (VMA and VFA)	VMA, VFA	0.00	1.11	228.5
ANN H. 2. 2. (3-30-30-1)	Without VFA	VMA, $\lvert G_b^*\rvert$, P_c	0.74	0.51	34.7
ANN H. 2. 3. (3-30-30-1)	Without VMA	VFA, $\lvert G_b^*\rvert$, P_c	0.73	0.52	34.3
ANN H. 3. 1. (1-30-30-1)	Contact factor	P_c	0.60	0.63	36.6
ANN H. 3. 2. (3-30-30-1)	Without contact factor	VMA, VFA, $\lvert G_b^*\rvert$	0.85	0.39	26.2

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Table 4. Sensitivity analysis results for ANN models using 7500 test data.

E* Predictive Models	Input parameter Property	Parameter	Goodness-of-fit in Arithmetic Scale R^2	Se/Sy	AAE (%)
Hirsch	Asphalt Binder, Volumetric, Contact Factor	VMA, VFA, $\|G_b^*\|$, P_c	0.23	0.88	50.6
ANN Hirsch (4-30-30-1)	Asphalt Binder, Volumetric, Contact Factor	VMA, VFA, $\|G_b^*\|$, P_c	0.83	0.41	28.6
ANN H. 1. 1. (1-30-30-1)	Asphalt binder	$\|G_b^*\|$	0.68	0.57	43.0
ANN H. 1. 2. (3-30-30-1)	Without asphalt binder	VMA, VFA, P_c	0.80	0.44	30.1
ANN H. 2. 1. (2-30-30-1)	Volumetric (VMA and VFA)	VMA, VFA	0.00	1.09	240.5
ANN H. 2. 2. (3-30-30-1)	Without VFA	VMA, $\|G_b^*\|$, P_c	0.74	0.51	34.7
ANN H. 2. 3. (3-30-30-1)	Without VMA	VFA, $\|G_b^*\|$, P_c	0.73	0.52	34.2
ANN H. 3. 1. (1-30-30-1)	Contact factor	P_c	0.58	0.65	38.7
ANN H. 3. 2. (3-30-30-1)	Without contact factor	VMA, VFA, $\|G_b^*\|$	0.85	0.39	25.3

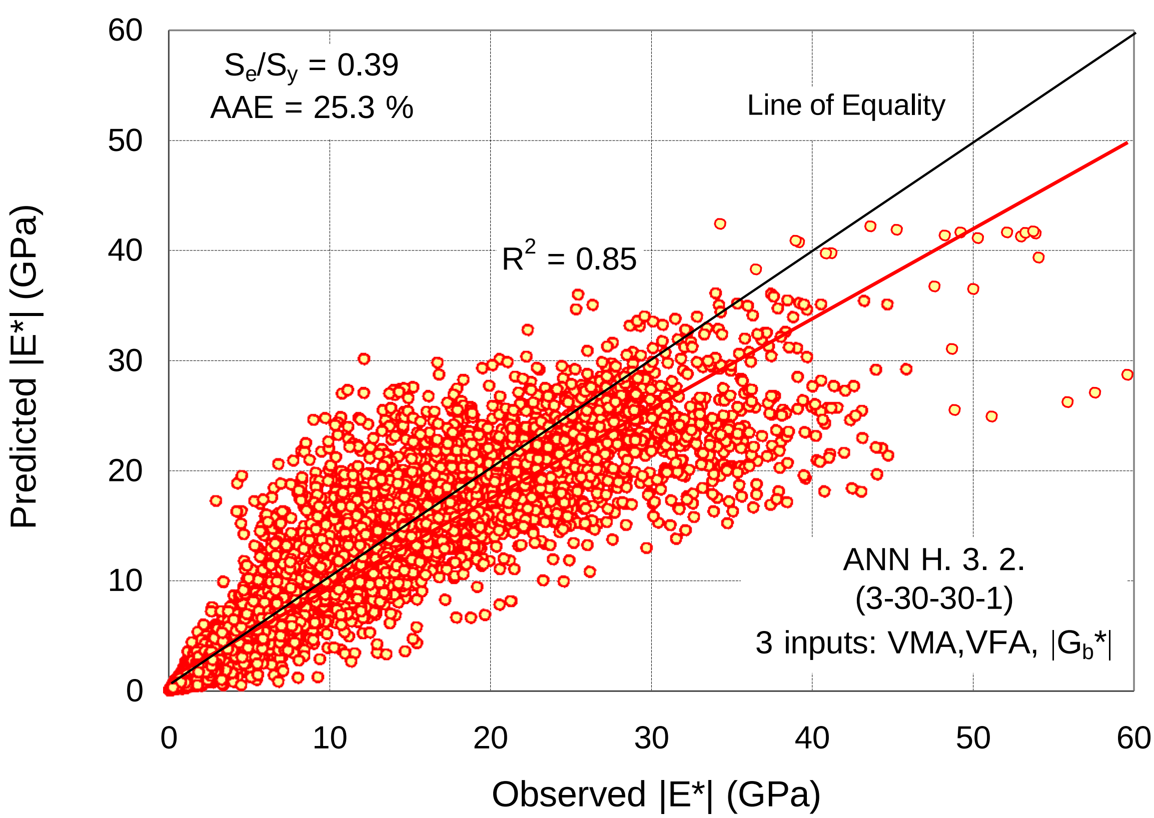

Fig. 7. Predicted versus observed |E*| using VMA, VFA, and $|G_b^*|$ inputs.

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Summary and Conclusions

This paper presented the development of a new HMA |E*| prediction model employing the ANN methodology. The ANN based |E*| prediction models were developed based on a comprehensive database of |E*| laboratory measurements that is currently available to researchers. The ANN model predictions were compared with the Hirsch |E*| prediction model. The sensitivity of input variables to ANN model predictions was examined. Based on the study findings, the following conclusions were drawn:

- The ANN based |E*| prediction models use the same input variables as the Hirsch |E*| prediction models, but make |E*| predictions with significantly higher accuracy.
- The Hirsh |E*| prediction models show bias at the lower or higher |E*| spectrum. This problem could be eliminated with the use of ANN |E*| prediction models which show no bias. This can lead to more accurate characterization of HMA dynamic modulus, better performance prediction, and reduce the risk of premature pavement failure.
- The ANN based |E*| prediction models are primarily influenced by asphalt binder properties ($|G_b^*|$), which is quite rational.
- The ANN based |E*| prediction models can capture the influence of non -asphalt binder property inputs (volumetric properties) on |E*| prediction.
- It was found that the ANN model can provide a good prediction of |E*| using only three variables ($|G_b^*|$, VMA and VFA).

Acknowledgments

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