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Development of Dynamic Modulus Predictive Model Using Artificial Neural Network (ANN)

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Dr. Souliman has participated in several state and national projects during his current employment at the University of Texas at Tyler including "Documenting the Impact of Aggregate Quality on Hot Mix Asphalt (HMA) Performance, Texas Department of Transportation" for TxDOT, "Mechanistic and Economic Benefits of Fiber-Reinforced Overlay Asphalt Mixtures" for Forta Corporation as well as "Simplified Approach for Structural Evaluation of Flexible Pavements at the Network Level" which was funded by the US Department of Transportation via Tran-SET University Transportation Center.

Dr. Souliman has more than 100 technical publications, conference papers and reports in the field of pavement and aggregate testing, characterization, and field monitoring. He is the recipient of the lifetime International Road Federation Fellowship in 2009. In 2017, his research work on pavement engineering-related projects earned recognition as his college's recipient of the Crystal Talon Award, sponsored by the Robert R. Muntz Library, recognizing outstanding scholarship and creativity of faculty from each college as determined by their dean. He also was awarded with the Crystal Quill award in 2018 by the University of Texas at Tyler for his research efforts and achievements.

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Development of Dynamic Modulus Predictive Model Using Artificial Neural Network (ANN)

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Abstract

In Mechanistic-empirical Pavement Design Guide (MEPDG), dynamic modulus |E*| is identified as a key property for Hot Mix Asphalt (HMA). Determining |E*| in the laboratory requires several days of sophisticated testing procedures and expensive instruments. To bypass the long testing time, sophisticated testing procedure, and expense, several multivariate regression analysis-based models have been developed to predict the dynamic modulus from simpler materials properties and volumetrics. Witczak 1999 and Modified Witczak 2006 are the two most widely used dynamic modulus predictive models in the asphalt community. Several other regression-based models have been developed earlier such as the Hirsch Model, the Law of Mixtures Parallel Model, and the Resilient Modulus-based Model. The highest R^2 value among all regression-based models is 0.87. Using Artificial Neural Network (ANN) a |E*| prediction model is developed in this study. To train the ANN model a dataset with 7400 data points is used, which is the same dataset used in the Modified Witczak 2006 model development. The overall R^2-value for the ANN model is 0.9 and is better than other regression-based models. The weights and biases' matrixes are reported to reproduce the model for future use. This model can replace the existing regression-based model for quick prediction of |E*| without performing any sophisticated test.

Introduction

Dynamic modulus is defined as the relation between the maximum stress and maximum strain of a viscoelastic material under continuous sinusoidal load. It is one of the most important properties to design, analyze and evaluate the performance of Hot Mix Asphalt (HMA). Several predictive models have been developed to predict the dynamic modulus from simple material properties and volumetric. The previous generation regression-based model performs well enough to be incorporated in the design manual. The equations developed through the regression-based model are easy to use. But they are underperforming in extreme temperature and extreme dynamic modulus values. The temperature also gets more importance in those multivariate regression-based models. The new generation machine learning-based models are showing promise and performing better in extreme. But they are not generating any equations to predict. To bridge the gap between these two methods, in this study an Artificial Neural Network (ANN) model has been developed to predict the dynamic modulus. Unlike the other ANN model, the wights and bias matrixes of the model are reported. Therefore, the model is reproducible and can be used for different data set.

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Literature Review

The total length of roads in the United States of America is 2.3 million miles. Approximately 96% of those roads have Hot Mix Asphalt (HMA) Surface[1]. Dynamic Modulus is an important property to design, analyze and evaluate the performance of HMA surface. Vander Poel of the Shell Oil Company introduced the term "stiffness" in the early 1950s[2]. As materials used in HMA are not purely elastic, the stiffness of HMA depends on loading time and the temperature of the mix. To represent the stiffness of HMA various parameters have been used, such as flexural stiffness, creep compliance, relaxation modulus, resilient modulus, dynamic modulus, etc.[3]. The universally used stiffness parameter is dynamic (complex) modulus (E*). One of the conclusions from the NCHRP 9-19 project is that Dynamic Modulus (|E*|) is a good performance indicator for HMA design and was recommended for Simple Performance Test (SPT)[4]. It is also recommended as quality control and quality assurance parameter[5]. It is the key property for HMA in Mechanistic-empirical Pavement Design Guide (MEPDG).

Dynamic Modulus |E*| is defined as the ratio between the amplitude of sinusoidal stress and amplitude of sinusoidal strain at the same time and frequency. HMA is a visco-elastic material. It's a stress-strain relationship under continuous sinusoidal loading is defined by the dynamic modulus. Determining Dynamic Modulus (|E*|) in the laboratory requires time, sophisticated procedures, and an expensive testing machine. Therefore, various predictive model has been developed to predict dynamic modulus from simple material properties and volumetric. Witczak 1999 and Modified Witczak 2006 are the two most widely used dynamic modulus predictive models in the asphalt community. Modified Witczak model was incorporated in MEPDG software along with the original 1999 Witczak equation[6]. Several other regression-based models have been developed earlier such as the Hirsch Model, the Law of Mixtures Parallel Model, and the Resilient Modulus-based Model. Several studies have concluded that regression-based multivariate models show significant scatter at low or high dynamic modulus |E*| values and the accuracy falls flat in low and high-temperature extremes[7,8,9,10,11]. Those models also tend to be dominated by the temperature as an input than the other input parameters[12]. Table 1 shows the R^2 values for all the regression models.

Table 1. Performance of Regression Bases Model for Predicting Dynamic Modulus[13]

Regression Model	**R^2**
Hirch (arithmetic scale)	0.871
Revised Hirsch (arithmetic scale)	0.874
Revised Bari-Witczak (arithmetic scale)	0.875
Al-Khateeb 1 (arithmetic scale)	0.817
Al-khateeb 2 (arithmetic scale)	0.869
NCHRP 1-40D (on logarithmic scale)	0.332
Simplified global (on logarithmic scale)	0.226
Bari-Witczak (on logarithmic scale)	0.584
Revised Bari-Witczak (on logarithmic scale)	0.856

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To overcome the shortcomings of the regression-based multivariate predictive model, Artificial Neural Network (ANN) based model is also developed[14,15]. Using the same input variables as used in the modified Witczak equation, the ANN models performed better in prediction. ANN models showed better prediction accuracy at extreme lows and highs than the regression-based models. They tend to have a better balance in giving priority to the temperature as an input than other input parameters. Various other approaches have been developed like using machine learning and computational micromechanics[16,17,18]. But all the models developed with machine learning worked as a black box. Sometimes their weights and biases' matrixes are not reported. Those models are not reproducible. In this study, an ANN-based model is developed, and the weights and biases of the model are reported. The main goal is to develop an ANN-based model which performs better than the regression-based models. Therefore, the minimum number of hidden layers and neurons are employed to build the model. The weights and biases are also reported. Therefore, the model can be used on other datasets to predict dynamic modulus.

Developing Model with Artificial Neural Network

The dataset used in developing the Witczak-Bari model is also used in this study in the training, validation, and testing process of the model. 7400 input data is used to predict the output data. The 7400-input data was collected from 346 mixes. The input variables were chosen as the same variables used in the Modified Witczak equation. The number of Input variables was eight and dynamic modulus was the target output in the training process. 7400 unique E* with eight input variables were fed into the network. Table 2 is showing all the variables in the training process.

Table 2. Variables Used in the Model

Variable Name	**Notation**	**Unit**
Percentage of aggregates (by weight) retained on ¾ inch sieve	ρ_{34}	%
Percentage of aggregates (by weight) retained on 3/8 inch sieve	ρ_{38}	%
Percentage of aggregates (by weight) retained on #4 sieve	ρ_4	%
Percentage of aggregates (by weight) passing through #200-inch sieve	ρ_{200}	%
Percentage of air voids (by volume)	V_a	%
Percentage of effective asphalt content (by volume)	Vb_{eff}	%
Dynamic shear modulus of binder	$\lvert G_b^*\rvert$	psi
Phase Angle of binder associated with $\lvert G_b\rvert$	(δ_{b}).	degree
Dynamic modulus	E*	psi

Different interconnected neurons work together to solve complex problems in Artificial Neural networks. The greater number of neurons and hidden layers give better results. But an increased number of neurons and hidden layers produce an overfitted model which does not perform well outside the training database. Therefore, one hidden layer is typically sufficient to solve most non-linear problems[19]. At first, the model was trained with one neuron in one hidden layer. The R^2 value was not sufficient for the model with a single neuron. Then the number of neurons was increased. If the R^2 value was not sufficient, then the number of neurons was increased again. After repeating this process for few times, the desired R^2 was achieved with 20 neurons in one hidden layer.

Out of the 7400 data points, 70% of the data was randomly selected and used as a training data set. The model was trained with the 5180 data points. The R^2 is 0.91 for the training dataset. The R^2 for

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the validation dataset was 0.89. 15% of the data points, which is 1110 points were used in the model validation process. For model validation, the main target was to optimize the Mean Squared Error (MSE). When the MSE value reached the minimum value, the training was stopped. Figure 1 shows that the least MSE value was reached after 187 iterations. The least MSE value was 2.2x 10^{11}.

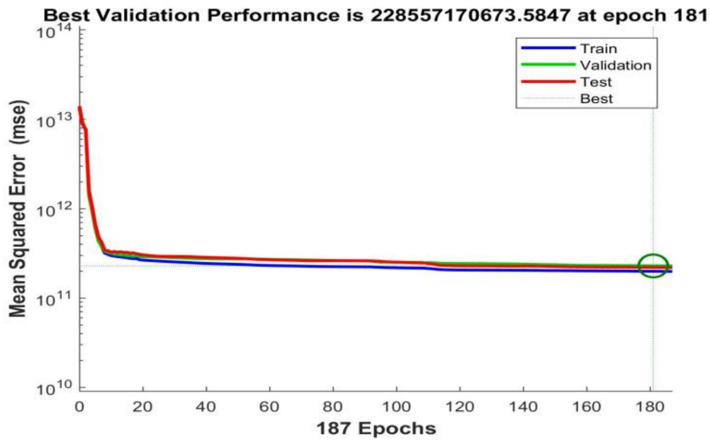

Figure 1. Validation of the ANN model in 187 epochs.

After completing the training and validation process, the model was tested on the remaining 15% data points. These 1110 data points were unknown to the model. The testing data was kept away from the model before testing. This testing process made the model robust against unknown data. The R^2 for testing was 0.90. Testing the model against unknown data protects the model from overfitting the model with the training dataset. Figure 2 shows that all three R^2 values in the training, validation and testing process are fairly close. The overall R^2 for the model is 0.9. This is better than any regression-based prediction model mentioned in Table1.

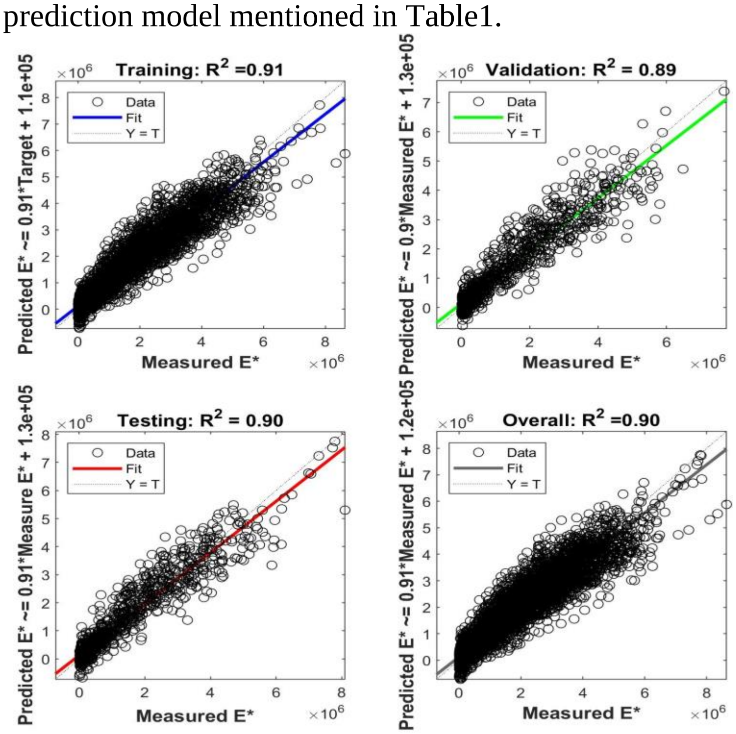

Figure 2. R^2 values in Training, Validation, Testing and Overall

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The ANN-based model is run by matrixes of weights and biases. The normalized input variables are multiplied by the weight matrix W_{ih} and the bias matrix b_{ih} is added with the product. After that, the product from the hidden layer is multiplied by the weight matrix $W_{ho,}$ and bias b_{ho} is added with the product. In this step, a normalized out is gained from the model. After denormalizing the output, the model provides the target output. Figure 3 shows the architecture of the ANN model developed in this study. All the matrixes for weights and biases are also reported below.

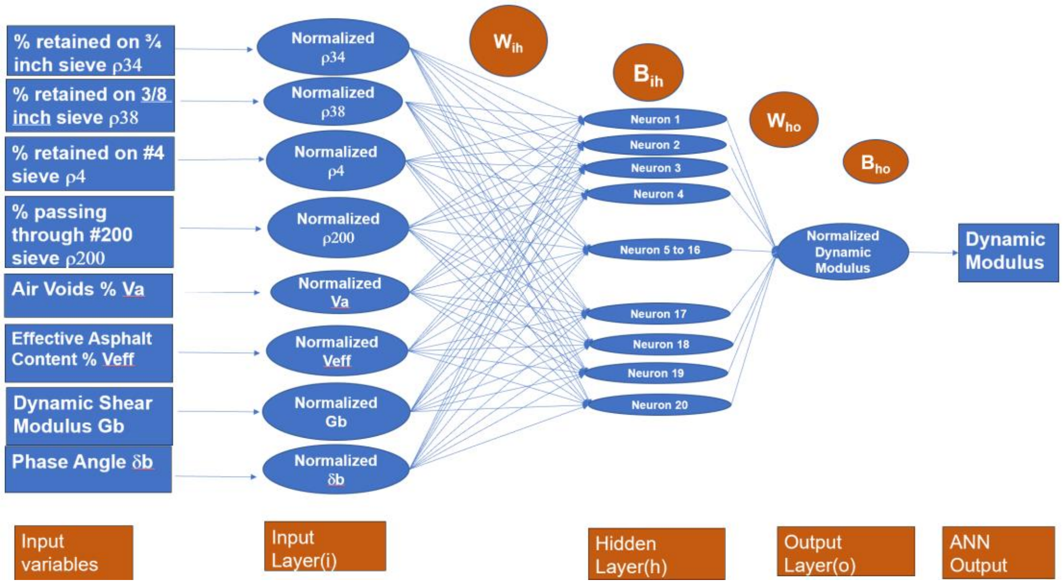

Figure 3. Architecture of the ANN-based Dynamic Modulus Prediction Model

	0.29215	2.85901	-0.07638	-1.24597	0.93330	3.33122	-0.08884	-0.26267
	0.88552	3.74619	-6.54191	-2.04369	-1.19882	-7.72302	1.91874	-1.23025
	-0.13862	0.78280	0.58535	-0.56057	2.39711	0.00381	0.44160	0.70837
Weights	-0.87278	0.75418	1.05796	-1.54662	-0.50222	-1.58830	-0.62947	-0.37123
for	-6.59999	-6.11600	-16.45912	-12.85108	3.35584	5.13716	0.31735	-0.98884
Input to	-3.68108	0.32216	4.89963	-4.27105	-0.91915	-0.26141	0.58768	0.09217
Hidden	-0.19185	-3.52012	0.11113	1.07106	-0.90254	-3.64307	-0.00770	0.22774
Layer	-1.31807	-9.47328	-3.66345	0.50221	0.22424	-6.62614	-0.55127	0.97766
$\mathbf{W_{ih}}$ =	-2.17382	1.19072	7.19416	2.66379	4.36667	-1.84596	1.35009	-0.73111
	-1.26529	-4.39237	7.08120	-5.04528	4.82078	-4.69730	-0.06433	-0.19913
	-1.46441	-9.74722	9.28093	-6.63405	-0.73764	-4.63959	0.20348	0.38662
	0.08794	-0.06233	-0.06126	-0.11862	0.10494	0.24015	0.71473	-1.33418
	-1.92693	2.43979	-8.60489	-8.26152	-0.63829	0.43640	0.28198	0.01332
	6.30896	6.44113	16.17857	13.19441	-3.35549	-4.95544	-0.30429	0.97204
	16.55955	0.14000	-4.35588	2.37729	-2.96943	-4.73150	-11.73132	-0.21176
	0.16664	-0.45681	5.49950	6.69828	2.22188	0.10980	-0.40303	0.13905
	-19.41615	18.64156	-14.05268	2.14252	3.79068	1.08215	-0.55314	1.29301
	-1.63538	14.18238	-2.40314	-0.77948	2.40239	-4.10070	0.79061	-2.16614
	0.09570	-0.05574	-0.06413	-0.12570	0.11467	0.28183	1.04686	-1.43687
	-0.09871	0.07992	0.06293	0.13594	-0.10934	-0.27419	-0.29971	1.62902

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Biases for Input to Hidden Layer		Weights for Hidden Layer to Output Layer		Biases for Hidden Layer to Output Layer	
b_{ih} =	-0.50427	W_{ho} =	3.624678	b_{ho}=	-1.28448
	-4.94848		-0.16163		
	0.918998		-0.27898		
	-0.2268		0.42097		
	-2.15554		4.846017		
	3.749635		-0.62366		
	0.321625		3.58437		
	0.079402		-0.17146		
	-0.80196		0.114938		
	-2.96723		0.124402		
	-5.81389		-0.18644		
	1.847841		23.7495		
	-0.0355		-0.22211		
	2.273769		4.895425		
	1.500197		-0.04863		
	0.303827		-0.27493		
	-0.90465		0.156574		
	-9.22379		0.213876		
	1.883526		-8.96053		
	-1.85333		13.29923		

The number of rows and columns in the first weight matrix W_{ih} represents the size of the network. The number of columns represents the number of input variables used. Here it is 8. The number of rows represents the neurons, used in the network. Here, the number of neurons used is 20. The input variables are put into the network after normalizing every input between the [-1,1] range. Normalizing the input protects the training process from overweighing the variable with a large value. After normalization, all variables are in the range of [-1,1]. The input variables are multiplied by the first weight matrix W_{ih} and the bias matrix b_{ih} is also added. The output from this process enters into the hidden layer and every value in the hidden layer is activated with the hyperbolic Tan function. From the hidden layer, the inputs are multiplied by the second weight matrix $W_{ho,}$ and bias b_{ho} is also added. After that the value is denormalized and the model gives the outcome. All the wights and the model in this study can be reproduced.

Summary and Conclusion

The ANN model in this study performed better than the existing regression-based models. The weights and biases' matrixes can be used to reproduce the model for further use. Even an equation with hyperbolic Tangent function can be produced from the matrixes. But it will be a lengthy equation as the number of equations will represent the number of lines in the equation. Future studies will tackle this issue with less number of neurons. One of the limitations of ANN based-model is that ANN can not extrapolate data. Therefore, it does not perform outside the range of the training dataset. Therefore, before applying this model on to any data, the range of the values of the variables should be checked first. But 7400 points cover a wide range. With R^2 = 0.9, this model can be used to predict dynamic modulus without going through laboratory procedures.

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