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Visco-Elastic Portrayal of Bituminous Materials: Artificial Neural Network Approach

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ABSTRACT: This paper presents a scheme to circumvent the need for extensive laboratory testing to determine the dynamic modulus of asphalt concrete materials. It calls for using existing complex modulus test results and applying an analytical tool to expand this data. This study presents the artificial neural network (ANN) technique as a promising method that can help designers have a good estimation of the dynamic modulus based on data accumulated over the years. The study highlights the use of ANN method, which utilizes simple physical parameters as input, to predict the dynamic modulus of asphalt concrete. Results of ANN simulations showed the ability of the ANN technique to predict the dynamic modulus of mixes prepared to different air voids and with different gradations and binders. Such a tool represents an attractive alternative to testing for small jurisdictions with limited budget and personnel.

INTRODUCTION

The new mechanistic–empirical pavement design guide (MEPDG), developed under the NCHRP project 1-37A, adopted the dynamic modulus to characterize the visco-elastic behavior of bituminous materials (NCHRP 2004). In level 1 of input, the dynamic modulus is determined in the laboratory, which requires special equipment and training of technical staff, a capability that the majority of road jurisdictions in Canada lack today. The complex and time consuming nature of the laboratory test motivated the developers of the MEPDG to introduce two more levels of inputs (level 2 and 3) which do not require testing to characterize asphalt concrete materials. In level 2 and 3, the dynamic modulus is estimated using a predictive model based on results of tests performed on binders, aggregate gradation and mix properties. Attempts to estimate the dynamic modulus using empirical predictive models fall short of providing accurate estimates of this parameter. Consequently, there is a need for an alternative to determine the dynamic modulus of asphalt concrete materials. This paper presents an approach that circumvents the need for extensive laboratory testing and overcomes the shortcoming of the empirical predictive models. The proposed scheme is based on combining the use of existing laboratory-generated data

with analytical modeling based on artificial neural network (ANN) to produce adequate estimate of dynamic moduli of asphalt concrete materials.

DYNAMIC MODULUS DETERMINATION

The complex modulus concept is used to evaluate the fundamental stress-strain response of asphalt concrete mixes. The modulus is a complex number, which defines the relationship between the stress and strain for a linear visco-elastic material subjected to a sinusoidal loading.

Laboratory Testing

Within the visco-elastic domain, the response of an asphalt concrete material subjected to a sinusoidal loading is also sinusoidal but with a phase lag (Sayegh 1967). Equations 1 to 4 describe the visco-elastic approach mathematically (Heck et al. 1998, Richard et al. 2003 and Sayegh 1967).

The applied stress function is given by:

$$\sigma = \sigma_0 \cdot e^{i\omega t} \quad (1)$$

and the corresponding strain is given by:

$$\varepsilon = \varepsilon_0 \cdot e^{i(\omega t - \phi)} \quad (2)$$

where σ_0 is the stress amplitude, ε_0 is the strain amplitude, ω is the angular velocity and ϕ is the phase angle describing the time that the strain lags the stress. The phase angle is an indicator of the degree of the visco-elastic behavior of asphalt concrete mix.

The complex modulus is defined (by analogy to the Young modulus of elasticity) as shown in Equation 3 (Witczak and Root 1974):

$$E^*(i\omega) = \frac{\sigma}{\varepsilon} = \frac{\sigma_0}{\varepsilon_0} e^{i\phi} = E_1 + iE_2 \quad (3)$$

where the real part of the complex modulus (E_1) is a measure of the material elasticity and the imaginary part (E_2) is a measure of its viscosity.

The ratio of the stress to strain amplitudes defines the absolute value of the complex modulus which is known as the dynamic modulus and is expressed by:

$$|E^*| = \frac{\sigma_0}{\varepsilon_0} \quad (4)$$

Predictive Modeling

While the determination of the dynamic modulus in the laboratory remains the most reliable means, many predictive models have been used to estimate this parameter based on the physical properties of the mix, aggregates and binder. The use of predictive models has been popular mainly due to the lack of laboratory equipment in addition to the highly demanding nature of the test. In the MEPDG, the predictive model used has this form (NCHRP 2004):

$$\log|E^*| = -1.249937 + 0.029232P_{200} - 0.001767(P_{200})^2 + 0.002841P_4 - 0.058097V_a - 0.802208 \frac{V_{beff}}{(V_{beff} + V_a)} + \frac{[3.871977 - 0.0021P_4 + 0.00395P_{38} - 0.000017(P_{38})^2 + 0.00547P_{34}]}{1 + e^{(-0.603313 - 0.313351 \log f - 0.393532 \log \eta)}} \quad (5)$$

where

$|E^*|$ = Asphalt mix dynamic modulus, in 10^5 psi,

η = Bitumen viscosity, in 10^6 poise,

f = Loading frequency, in Hz,

V_a = Percent air voids in the mix, by volume,

V_{beff} = Percent effective bitumen content, by volume,

P_{34} = Percent retained on 3/4-inch sieve, by total aggregate weight (cumulative),

P_{38} = Percent retained on 3/8-inch sieve, by total aggregate weight (cumulative),

P_4 = Percent retained on No. 4 sieve, by total aggregate weight (cumulative), and

P_{200} = Percent passing No. 200 sieve, by total aggregate weight.

Zeghal et al. (2005) assessed the capabilities of this predictive equation in estimating the dynamic modulus. They concluded that the predictive equation came short of accurately predicting the dynamic modulus measured in the laboratory. An average absolute relative error of 77% was reported. The shortcomings of the predictive model motivated the search for other alternative methods to determine the dynamic modulus of asphalt concrete materials.

ARTIFICIAL NEURAL NETWORK MODELING

The ANN technique is a relatively new method of modeling that was originally presented by Ghaboussi et al. (1990 and 1991). Unlike other modeling techniques that rely on mathematical expressions to describe experimental observations, ANN modeling relies on the learning capabilities of its elements.

An ANN model is a collection of interconnected elements (neurons) that are linked together in a way similar to the architecture of the human brain and have the performance characteristics of biological neurons (Fausett 1994). It is capable of recognizing, capturing and mapping features (known as patterns) contained in a set of data mainly due to the high interconnections of neurons that process information in parallel. The learning capabilities allow neural networks to be directly trained with the results of experiments. Once an ANN model has learned the patterns defining the relationship between the input and output of a certain test or process, it can generalize from its training set data to novel cases. Presenting a network with facts for which the input and output are known to delineate the embedded patterns is an integral part of the ANN modeling process.

An ANN model is made up of at least three layers. The first layer contains the input parameters while the last layer contains the output (solution). One or more layers known as hidden layers are usually placed between the input and output layers. The hidden layers constitute the network's means of delineating and learning the patterns governing the data that the network is presented with.

There are many ways a neural network can be trained. The back propagation technique is the most popular process and has been used in many fields of science and engineering such as construction simulation (Flood 1990 and Moselhi et al. 1991), constitutive modeling (Rogers 1994) and structural analysis (Garrett et al. 1992). In a back propagation learning process, training is accomplished by assigning random connection weights to the connections and calculating the output using the present connection weights. At a second stage, the process involves back propagating the error defined as the difference between the actual and computed output through the hidden layer(s). This procedure is repeated for all training facts until the error is within a certain tolerance. The final network with final connection weights is then saved to serve as a prediction model.

Architecture and Optimization

The development of an ANN model involves defining the number of nodes in the input, output and one or more hidden layers. The input layer size is generally predetermined based on the parameters known or assumed to affect the targeted output. However, the number of hidden layers as well their nodes is usually determined by a trial-and-error procedure. Determination of the number of hidden layers and their nodes involves training and testing the built network against test sets made of examples with known input and output.

Using a subset of laboratory-determined dynamic modulus values used in the calibration of the MEPDG (NCHRP 2001), an ANN investigation was initiated to examine the effectiveness of the analytical technique in expanding the database without the need for further testing. The laboratory data used in this study included experimental results of complex modulus test performed on 42 mixes. The laboratory database included dynamic modulus values of mixes covering a wide range of air voids (4.0% to 11.0%). These mixes also enveloped different binders, with a wide range of high temperature (75 to 52) and low temperature (−10 to −34) performance grades, and binder content (3.6% to 6.4%). The data also reflected mixes with different aggregate characteristics as shown in Table 1.

Table 1. Characteristics of Aggregates

	Percent passing No. 200 sieve	Percent retained on No. 4 sieve	Percent retained on 3/8-inch	Percent retained on ¾-inch sieve
Maximum value	7	60	97	100
Minimum value	3	27	60	78

In this study, the dynamic modulus is the single targeted output. The inputs included the major parameters known to affect the visco-elastic behavior of asphalt concrete, namely, the binder performance grade, the binder content by weight, the mix's air voids, the four aggregate characteristics shown in Table 1, temperature and frequency. The number of nodes in the hidden layer(s) was investigated in order to arrive at a

robust network. The investigation consisted of training ANN models with varying number of hidden layers and nodes. Ten percent of the data was randomly set aside for testing the trained network and another ten percent of the data was reserved for comparing the predictions of the built network with laboratory obtained data. The effect of the number of hidden nodes on the accuracy of the network was measured by the percentage “Absolute value of the Relative Error” (|ARE|) defined as:

$$|ARE| = \text{abs.} \{ (X_{\text{prediction}} - X_{\text{actual}}) / X_{\text{actual}} \} \times 100\% \quad (6)$$

Through trial-and-error, it was found that using more than one hidden layer did not improve the accuracy of the predictions as depicted by the typical results obtained for a network consisting of two hidden layers and for which the first hidden layer (H1) had 14 nodes (see Figure 1). Consequently, the number of nodes in the single hidden layer was the only parameter left to be determined. The effect of the number of hidden nodes in the single hidden layer on |ARE| is also displayed in Figure 1. It shows that the number of nodes in the hidden layer plays a major role in the accuracy of the network. Further, the network consisting of 20 nodes in the single hidden layer was found to provide the best accuracy with an |ARE| of about 17%, which was considered acceptable since it was observed that replicate samples tested in the laboratory might exhibit a difference in the order of 10 to 20%.

FIG. 1. Optimizatin of the ANN model.

Adequacy

Once the ANN structure was optimized, the ability of this technique to learn the features known to affect the visco-elastic behavior of asphalt concrete materials and embedded in the training data was checked. The optimized network was used to check trends related to variations in temperature and frequency. Predictions generated by the

ANN model were checked against trends established in the literature for these two variables. Figure 2 shows the results of ANN predictions obtained for an asphalt concrete mix prepared to an air void of 5.2% using a neat binder (PG 58-22) and a binder content of 5.0%. It is clear that the ANN model is capable of reproducing the known effect of temperature and frequency. At all frequencies, a decrease in the temperature results in an increase in the dynamic modulus. Further, at any temperature, an increase in frequency yields an increase in the dynamic modulus.

PREDICTION OF DYNAMIC MODULI

The ability of the ANN technique to predict the dynamic modulus in a satisfactory manner was determined by comparing ANN predictions and laboratory results of several asphalt concrete mixes that the model did not see before. A typical comparison done for a mix (for which the binder performance grade was PG 52-34, the binder content by weight was 5.2% and the air voids were 6.0%) is presented in Table 2. The gradation characteristics of this mix are shown in Table 3. Table 2 indicates that the ANN technique is capable of predicting the dynamic modulus with satisfactory accuracy. The $|ARE|$ of the 2/3 of predictions were lower than 15%. Further, with the exception of few data points, the predictions of the optimized ANN had an $|ARE|$ consistently lower than 25%, which is much lower than the error encountered when the predictive model was used (77%).

FIG. 2. Effect of temperature and frequency on the dynamic modulus.

Table 2. Typical |ARE| Obtained with ANN Predictions

Frequency (Hz)	Temperature (°C)	ARE (%)
0.1	-17.7	11
1	-17.7	14
10	-17.7	10
25	-17.7	14
0.1	4.4	13
1	4.4	28
10	4.4	15
25	4.4	12
0.1	21.2	23
1	21.1	24
10	21.1	20
25	21.1	6
0.1	37.8	33
1	37.8	3
10	37.8	10
25	37.89	25

Table 3. Typical Gradation Characteristics Used in ANN Predictions of Dynamic Moduli

Percent passing No. 200 sieve	Percent retained on No. 4 sieve	Percent retained on 3/8-inch sieve	Percent retained on 3/4-inch sieve
7.0	44	81	97

CONCLUSIONS

The mechanistic-empirical pavement design guide requires the use of the dynamic modulus to characterize bituminous materials. However, the dynamic modulus test is complex and time consuming. In addition, only few Canadian jurisdictions have the required testing capabilities and human resources to perform such a test. The adoption of the design guide will be hampered by such limitations unless other options are made available to generate such material input. This paper presented the artificial neural network as an alternative to performing the test to cover the wide spectrum of factors that are known to influence the dynamic modulus. Results obtained from the current study showed that the ANN technique is a valuable tool that has the capability of learning trends observed in laboratory testing of asphalt concrete and satisfactorily predicting the dynamic modulus of bituminous materials. Further, artificial neural network models were found to yield better accuracy than the empirical predictive equation adopted in MEPDG, which was developed using statistical analysis. Overall, an absolute average relative error lower than 25% was observed when the ANN model was used, which is about the third of the 77% error obtained when the predictive equation was employed.

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