The Estimation of the Dynamic Modulus of Asphalt Mixtures Using Artificial Neural Networks

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ABSTRACT: The dynamic modulus is the main input material property of asphalt mixtures for the modern mechanistic-empirical asphalt pavement design methods. The dynamic modulus is determined in laboratory by different procedures but in all cases, they require sophisticated equipment and well-trained personnel. When these experimental results are not available, they could be estimated using different predictive models based on the aggregate gradation, volumetric properties of the mixture and binder characteristics. This paper presents the application of the Artificial Neural Network (ANN) technique in order to develop a robust prediction model of the dynamic modulus of asphalt mixtures. The experimental data used for the training and validation processes were collected from different construction projects in Argentina. The measured and estimated dynamic modulus results using the ANN model were compared and discussed showing that the ANN model developed in this study is promising to estimate the dynamic modulus of bituminous mixes for practical applications.

KEY WORDS: Dynamic Modulus, Asphalt Mixtures, Neural Networks, Predictive Models.

1 INTRODUCTION

The dynamic modulus is the main input material property of asphalt mixtures for the modern mechanistic-empirical flexible pavements design methods. It determines the distribution of stress and strains into the pavement structure and also, it can be correlated with the rutting and fatigue cracking behavior of the bituminous layers (NCHRP, 2004).

The dynamic modulus E* is determined in laboratory by different procedures but in all cases, they require sophisticated equipment and well-trained personnel. Currently, few jurisdictions in Argentina have the required testing capabilities to experimentally determine the dynamic modulus of their asphalt mixtures and other alternatives are needed to obtain this property. When these equipments are not available, the dynamic modulus of the asphalt mixtures could be estimated with different predictive models developed by different researchers and based on the volumetric properties of the mixture, the aggregate gradations and the binder characteristics using regression analysis from experimental data.

A previous work (Martinez & Angelone, 2009) has reviewed three estimation procedures considering their advantages and disadvantages in terms of necessary inputs and ease of use.

This study concluded that, when testing results are not available, reliable first order dynamic modulus estimates for asphalt mixtures typically used in Argentina can be obtained using any of the predictive procedures considered. However, the predictive capabilities of each one could be improved using additional information, changing the functional form of the model or calibrating them.

Thus, in order to develop a more robust predictive model of the dynamic modulus of asphalt mixtures, a different point of view was considered at the Road Laboratory of the University of Rosario using the Artificial Neural Network (ANN) technique. Such an approach has been used successfully in other engineering fields like the analysis of building damages, identification of structural systems, behavior of materials, structural optimization and performance of building foundations. In road engineering, the technique was used in the back calculation of asphalt pavements (Kim, 2001; Meier, 1995; Ceylan et al, 2007), the predictions of roughness deterioration (Attoh-Okine, 1994), the estimation of the properties of asphalt mixtures (Far et al, 2009; Zeghal, 2008a; Zeghal, 2008b; Lacroix, 2008; Sakhaei Far, 2009) and subgrade soils (Zeghal y Khogali, 2005).

This paper presents the application of the Artificial Neural Network (ANN) technique in order to develop a robust prediction model of the dynamic modulus of asphalt mixtures. The primary advantage of this approach over statistical regression techniques is that the functional form of the relationships is not needed a priori and it offers the potential for capturing complicated nonlinear relationships between the dynamic modulus and mixtures variables. However, the main disadvantage of the ANN approach is the inability to extrapolate results when the inputs are outside the range of values used to develop it. The experimental data used for the training and validation processes were collected from different construction projects in Argentina. The measured and estimated dynamic modulus results using the ANN model are compared and discussed. Also, the accuracy of the predictions using the ANN model is compared against those obtained with another predictive procedure.

2 ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are computational systems made of a number of neurons that are connected together in a way similar to the architecture of the human brain. This system is capable of recognizing, capturing and mapping patterns contained in a set of data due to the high interconnections of neurons processing information in parallel. When a network has learned the patterns defining the relationship between the input data and output, it can be used to predict new conditions. A basic network is composed by three or more layers. The first layer contains the input data while the last layer contains the output result. One or more layers known as hidden layers are placed between the input and output layers. These hidden layers constitute the network's means of delineating and learning the patterns governing the data that the network is presented with. A basic architecture of an ANN with three neurons in the input layer, two neurons in the hidden layer and one neuron in the output layer is presented in Figure 1.

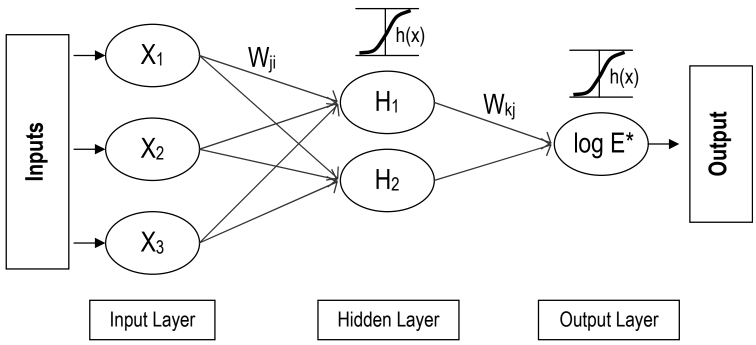


Figure 1: Schematic architecture of an ANN

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 named as learning process. In this study, the back propagation learning process has been adopted to train the network because it is the most popular process used in many fields of science and engineering. In a back propagation learning process, training is accomplished by assigning random connection weights to the connections between neurons and calculating the output using the present connection weights. Then, the process involves back propagating the error defined as the difference between the actual and computed output through the hidden layer. This procedure is repeated for all training sets of data until the error is within a certain tolerance. The final network with final connection weights is then saved to serve as a prediction model.

A more detailed description of the ANN technique is out of the purposes of this paper and more information could be found in Müller et al., 1995.

3 MATERIALS AND PROCEDURES

3.1 Materials

The materials used in this study were cores obtained from 17 different sections of asphalt pavements recently built around Rosario in the Littoral region of Argentina. In these sections, 33 locations were selected where asphalt concretes with different formulations were used for the surface and the base layers in order to obtain 51 different asphalt mixtures conventionally used in Argentina for surface and base layers of asphalt pavements. All of these mixtures can be classified as dense graded asphalt concretes with conventional binders. At each location, six cores were taken. Two of these cores were used for the determination of the dynamic modulus as is described later. The other four cores were used in the laboratory for the determination of the volumetric properties of each mixture, the properties of the recovered binders (viscosity at different temperatures, penetration and softening point) and the aggregate gradation. A database containing the information of the 51 mixtures was elaborated covering a wide range of properties used as inputs for the ANN predictive model. Table 1 presents a summary of the descriptive statistics calculated from the database, for the parameters considered in it.

Table 1: Descriptive Statistics of the mixtures and binder data

Variable		Values in the database			
		Maximum	Minimum	Average	Std. Dev.
Asphalt Binder	Viscosity 60 °C (Poises)	10200	2737	6605	1918
	Pen 25 °C (1/10 mm)	62.9	54.0	59.5	2.2
	Softening Point (°C)	67.7	32.3	43.0	8.3
Volumetric Properties	Vb (%)	14.1	10.0	12.5	0.9
	Va (%)	10.0	1.9	4.1	1.6
	VMA %	22.1	13.3	16.7	1.6
	VFA %	86.8	54.7	75.6	7.0
Aggregate Gradation	% passing #3/4	100.0	90.7	97.0	2.4
	% passing #3/8	84.3	59.7	75.3	5.7
	% passing #4	68.1	46.7	59.4	4.9
	% passing #8	51.6	34.6	43.1	4.0
	% passing #40	29.7	18.0	24.5	2.6
	% passing #200	9.0	4.5	7.3	0.9

with
Vb : Effective bitumen content by volume

Va : Air Voids content
VMA : Voids in the mineral aggregate
VFA : Voids filled with asphalt

3.2 Dynamic Modulus Determination

The Dynamic Modulus E* of the cores was experimentally measured with the Indirect tension (IDT) mode with sinusoidal loadings following a procedure very similar as it was developed by Kim et al., 2004 using the linear viscoelastic solution. These authors concluded that the IDT testing of cores seems to be more appropriate for the evaluation of existing pavements given that a typical asphalt layer thickness is less than 100 mm and that coring is the most effective method of obtaining specimens from actual pavements. Also, the dynamic modulus determined from the IDT test using this linear viscoelastic solution is statistically the same as the one measured from the axial compression test.

Assuming the plane stress state, the linear viscoelastic solution for the dynamic modulus of an asphalt mixture under the IDT mode results:

$$E^* = \frac{P}{\Delta h \, . \, t}\left(K_1 + \mu \, . \, K_2\right) \qquad (1)$$

where
E* : dynamic modulus
P : amplitude of the applied sinusoidal load
Δh : amplitude of the resulting horizontal deformation
t : thickness of specimen
K1, K2 : coefficients depending on the specimen diameter and gauge length
μ : Poisson's ratio

Testing was performed using a servo-pneumatic machine, developed at the Road Laboratory of the University of Rosario, using a 5000 N load cell, which is capable of applying load over a range of frequencies ranging from 0.01 Hz to 5 Hz. A proportional valve controlled by the computer is used to generate the sinusoidal loadings at the required frequency. The test frame is enclosed into a temperature chamber. The temperature control system is able to achieve the required testing temperatures ranging from 0 °C to 50 °C. The data acquisition system was also developed at the Road Laboratory of the University of Rosario and is capable of measuring and recording data from three channels simultaneously: two for horizontal displacements and one for the load cell. In order to increase the simplicity of the test, only horizontal deformations were measured and the Poisson's ratio was adopted as a function of the test temperature. The horizontal deformations were measured using LVDTs mounted on each of the specimen faces using a 35 mm gauge length. The applied load and the average horizontal deformation were calculated fitting sinusoidal functions to the measured experimental data. For the adopted gauge length and for specimens with 100 mm diameter, the coefficients K1 and K2 result: K1 = 0.188 and K2 = 0.595. The cores used for the determination of the dynamic modulus were trimmed to the test thickness approximately equal to 50 mm using a laboratory concrete saw. In this study, four temperatures (10, 20, 30 and 40 °C) and five frequencies (4, 2, 1, 0.5 and 0.25 Hz) were used. Then, the average of the experimental values of the two samples coming from the same location was considered in order to build a database containing 1020 experimental dynamic modulus values (51 mixtures, 4 temperatures and 5 frequencies).

4 DEVELOPMENT OF THE ANN MODEL

The architecture of the network is defined by the number of layers and neurons in each layer. In general, a great number of processes can be modeled with one or two hidden layers and then, only one hidden layer was selected for the development of this ANN predictive model.

Thus, a three layer feedforward neural network with supervised learning was trained with the experimental data. The available data has been randomly divided in two separated sets of values: the Training Pattern containing 80 % of the available data and the Validation Pattern with the remaining 20% of the data. As the dynamic modulus could vary in a wide range of values depending on the test temperature and the frequency (from 100 to 20000 MPa for conventional mixtures), E* values were considered in logarithmic values. The neural network expects any input and output value to be between 0 and 1. Therefore the pattern sets must be normalized before being processed by the network and this normalization was calculated as:

$$N(i) = \frac{(i - low)}{(high - low)} \quad (2)$$

with

i	: input or output value
low	: minimum possible value
high	: maximum possible value
N(i)	: normalized input or output value

Regarding the number of neurons in each layer, the input layer has 15 neurons: 13 neurons for the variables cited in Table 1 and 2 additional neurons for the testing temperature and the frequency. The output layer has only one neuron corresponding to the log E* value. The number of neurons in the hidden layer was analyzed in order to arrive at a robust network. The analysis consisted of training ANN models with varying number of neurons in the hidden layer and the effect of the number of hidden neurons on the accuracy of the network was measured by the average deviation AvDev between real and estimated values. This average deviation is calculated as:

$$AvDev = \frac{\sum_{i=1}^{N} (O_i - ONET_i)^2}{N} \quad (3)$$

where

AvDev	: average deviation
O_i	: real output value (normalized)
$ONET_i$	: estimated output value (normalized)
N	: number of values in the pattern

The effect of the number of hidden neurons in the single hidden layer on the average deviation using the training pattern is shown in Figure 2.

This figure shows that the number of neurons in the hidden layer plays a major role in the accuracy of the network. Further, the network with 13 neurons in the single hidden layer was found to provide the best accuracy with an average deviation approximately equal to 0.001, which was considered acceptable. Increasing the number of neurons in the hidden layer does not improve significantly the predictive quality of the model. Finally, only one hidden layer with 13 neurons was adopted for the development of this ANN predictive model.

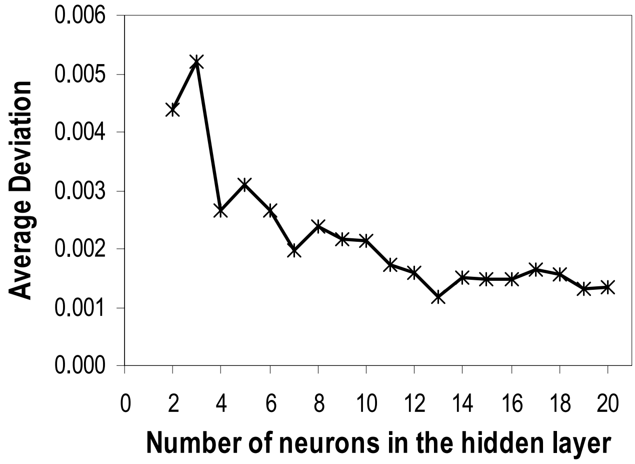


Figure 2: Evolution of the average deviation with the number of hidden neurons

5 OBTAINED RESULTS

5.1 Accuracy of the ANN model

The developed ANN model was trained and validated using a free software available on Internet that allows the user to import data from other spreadsheets, modify some control parameters and display real and estimated results in a comparative manner (Runtime Software, 2009).

In order to evaluate the accuracy of the predictions, the relative errors between measured (real) and estimated values has been calculated as:

$$\text{Relative Error} = \left| \frac{(E^*_i - E^*NET_i)}{E^*_i} \right| \tag{4}$$

with

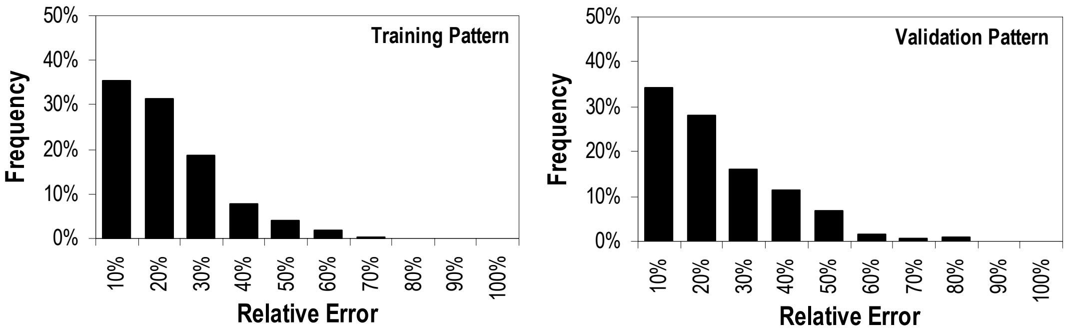
E^*_i : measured value of E*

E^*NET_i : ANN estimated value of E*

Figure 3(a) shows the frequency distribution of these relative errors for all the data in the training pattern while Figure 3(b) shows the same distribution for the validation pattern. As can be observed, approximately 85 % of the estimated values have a relative error smaller than 30 % for the training pattern while 80 % of the estimated values have a relative error smaller than the same limit for the validation pattern. These errors were considered very acceptable since it was observed that replicate samples tested in the laboratory might exhibit a difference in the order of 20 to 30 %.

5.2 Adequacy of the ANN model

Once the ANN model was trained, it was implemented on an Excel spreadsheet where, for a given set of inputs, the resulting E* value is automatically calculated. Then, the network was used to check trends related to variations in testing temperature and frequency. The predictions given by the ANN model were checked against trends established in the literature for these two variables using the characteristics of a novel asphalt mixture that the ANN model did no see before.



(a) (b)

Figure 3: Frequency distribution of the relative errors. (a) for the Training Pattern (b) for the Validation Pattern

The variables for this mixture are listed in Table 2. Also, temperatures and frequencies were different than those used in the experimental determination of E*. The ANN estimated E* values are shown in Figure 4.

Table 2: Variables of the novel mixture

Viscosity 60 °C (Poises)	4210
Pen 25 °C (1/10 mm)	53.0
Softening Point (°C)	53.1
Vb (%)	12.5
Va (%)	4.1
VMA %	16.5
VFA %	75.7

Gradation	
% passing #3/4	100.0
% passing #3/8	75.6
% passing #4	62.9
% passing #8	46.5
% passing #40	21.3
% passing #200	9.6

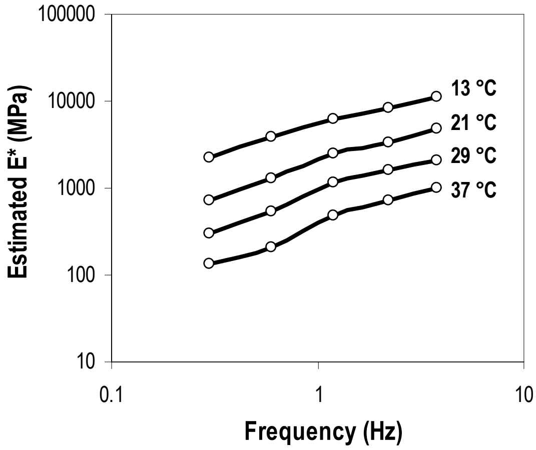


Figure 4: ANN estimated E* values

It is clear that the ANN model is capable of reproducing the known effect of temperature and frequency because at all frequencies, a decrease in the temperature results in an increase in the dynamic modulus and, at any temperature, and increase in frequency results in an increase in the dynamic modulus.

5.3 Comparisons with other predictive model

The ability of the ANN model to predict sufficiently accurate and reasonable dynamic modulus estimates adequate for use in mechanistic-empirical pavement design procedures was determined by comparing ANN estimations and predicted values using another well accepted prediction model (the Witczak model) included in the Mechanistic Empirical Pavement Design Guide developed under the project NCHRP 1-37A (NCHRP 2004). The model is formulated as:

$$\log E^* = 3.750063 + 0.02932\ p200 - .001767\ (p200)^2 - -0.002841\ p4 - 0.058097\ Va$$
$$- 0.802208\left(\frac{Vb}{Vb + Va}\right) + \frac{3.871977 - 0.021\ p4 + 0.003958\ p38 - 0.000017(p38)^2 + 0.00547p34}{1 - e^{[-0.603313 - 0.31335(\log f) - 0.393532(\log \eta)]}} \tag{5}$$

with

E^* : dynamic modulus in 10^5 psi

η : bitumen viscosity at the test temperature in 10^6 Poises

f : loading frequency in Hz

p34 : cumulative percent retained on the #3/4 sieve

p38 : cumulative percent retained on the #3/8 sieve

p4 : cumulative percent retained on the #4 sieve

p200 : percent passing the #200 sieve.

For the comparisons, the dynamic modulus values in psi were converted to MPa. Figure 5 shows the comparison between measured and estimated E* values using the ANN model while Figure 6 shows the same comparison using the predicted values with the Witczak model, [(a) in logarithmic space; (b) in arithmetic space].

To evaluate the performance of the predictive procedures, the correlation of the measured and predicted values was assessed using goodness-of-fit statistics according to subjective criteria proposed by Witczak et al., 2002, and shown in Table 3. The statistics include correlation coefficient, R^2 and Se/Sy (standard error of estimate values/standard deviation of measured values). Table 4 presents the evaluation of both predictive procedures according to these criteria.

Table 3: Criteria for Goodness-of-Fit Statistical Parameters

Criteria	R^2	Se/Sy
Excellent	≥ 0.90	≤ 0.35
Good	0.70 – 0.89	0.36 – 0.55
Fair	0.40 – 0.69	0.56 – 0.75
Poor	0.20 – 0.39	0.76 – 0.89
Very Poor	≤ 0.19	≥ 0.90

The ANN model has an excellent correlation to the measured dynamic modulus values and the goodness-of-fit statistics show an excellent performance, better than the performance of the predictions with the Witczak model. The predicted values using the ANN model are in excellent agreement for the full range of E* values measured for both, the training and the validation patterns. However, the Witczak model is in good agreement for medium and high values of the dynamic modulus but the lower modulus values are overestimated.

Based on the obtained results, it could be concluded that when testing results are not available, reliable first order dynamic modulus estimates for mixtures typical to Argentina can be obtained using the ANN model developed in this study.

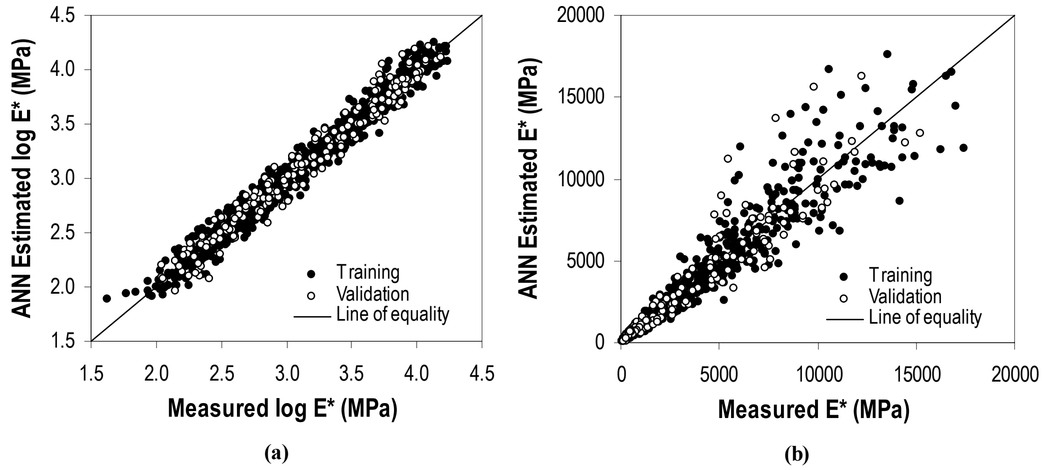


Figure 5: Comparison of E* values using the ANN model

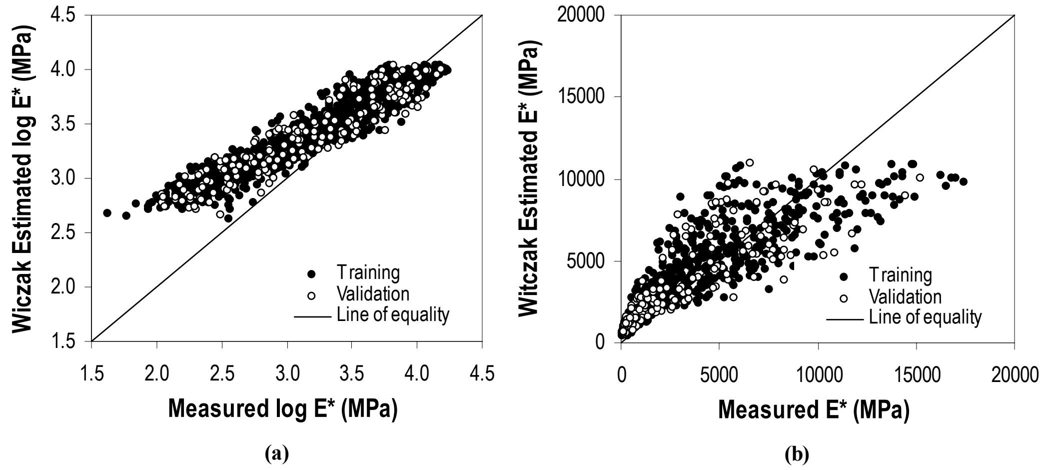


Figure 6: Comparison of E* values using the Witczak model

Table 4: Goodness-of-Fit Statistics for the Predictive Procedures

Pattern	Space	Statistics	ANN model	Witczak model
Training	Arithmetic	R^2 - Se/Sy	0.92 – 0.28	0.78 – 0.37
		Evaluation	Excellent/Excellent	Good/Good
	Logarithmic	R^2 - Se/Sy	0.97 – 0.16	0.90 – 0.20
		Evaluation	Excellent/Excellent	Excellent/Excellent
Validation	Arithmetic	R^2 - Se/Sy	0.90 – 0.34	0.72 – 0.43
		Evaluation	Excellent/Excellent	Good/Good
	Logarithmic	R^2 - Se/Sy	0.97 – 0.18	0.87 – 0.23
		Evaluation	Excellent/Excellent	Good/Excellent

6 CONCLUSIONS

The dynamic modulus is the main input material property of asphalt mixtures for the modern mechanistic-empirical flexible pavements design methods. However, the dynamic modulus test is complex and time consuming. In Argentina, there are only few laboratories with the required testing capabilities and human resources to perform such a test. This paper presented the development of a predictive dynamic modulus model based on the artificial neural network (ANN) technique. The results obtained in this study showed that the model has the capability of learning trends observed in laboratory testing of asphalt concrete and satisfactorily predicting the dynamic modulus of bituminous materials. The ANN model was found to perform better than the empirical predictive equation adopted in the Mechanistic Empirical Pavement Design Guide developed under the project NCHRP 1-37A. Finally, when testing results are not available, reliable first order dynamic modulus estimates for asphalt mixtures typically used in Argentina for practical purposes in mechanistic empirical pavement design procedures, can be obtained using the ANN model developed in this study.

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