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Modeling the Creep Compliance of Asphalt Concrete Using the Artificial Neural Network Technique

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ABSTRACT: The new mechanistic–empirical pavement design guide developed under the NCHRP project 1-37A adopted the creep compliance parameter to characterize the low-temperature behavior of bituminous materials. It is used to predict thermal cracking of roads. However, determination of the creep compliance at three temperatures (-20, -10 and 0°C) involves elaborate laboratory testing and special training of technical staff, a capability that the majority of road jurisdictions in Canada lack today. This paper presents a scheme to estimate the needed parameter by taking advantage of the wealth of field information available from long term pavement performance (LTPP) sites. The proposed technique is based on the use of artificial neural network technique to have a good estimation of the creep compliance of asphalt concrete mixes. Several ANN models were trained and tested using simple parameters collected over the years from LTPP sites. Results of ANN simulations showed the good potential that proposed model has to predict the creep compliance (at different low temperatures) of mixes prepared with different binders. Such a model represents an attractive alternative to testing for small jurisdictions with limited budget and personnel.

INTRODUCTION

The creep compliance was adopted in the mechanistic–empirical pavement design guide (MEPDG) developed under the NCHRP project 1-37A. It is mainly used to describe the behavior of asphalt concrete at low temperatures, which is used in the performance model to predict thermal cracking (NCHRP 2004). In level 1 of input, the creep compliance is determined in the laboratory at three different temperatures (0°C, -10°C and -20°C), which requires special equipment and training of technical staff, a capability that only few road jurisdictions in Canada possess. In level 2 of input, MEPDG recommends testing at one temperature (-10°C) only. In level 3 of input, MEPDG offers default values of creep compliance based on the binders' classification. Given the limited number of jurisdictions with laboratory-testing capabilities, there is a need for an alternative to determine the creep compliance of asphalt concrete materials. This paper presents an approach that circumvents the need

for laboratory testing and overcomes any shortcomings that the use of default values may introduce in the design of roads. The scheme is based on combining the use of existing laboratory-generated data with analytical modeling based on artificial neural networks (ANN) to produce adequate estimate of the creep compliance of asphalt concrete.

CREEP COMPLIANCE DETERMINATION IN THE LABORATORY

The creep compliance is determined in the laboratory using the indirect tensile creep (ITC) test following AASHTO T 322 standard. It is defined as the time-dependent strain exhibited by an asphalt concrete divided by the applied stress.

The ITC test is conducted by applying a fixed load to produce a horizontal deformation between 0.00125 mm and 0.0190 mm during the test (see Figure 1). Maintaining the strain between these two limits avoids the problem of a non-linear response by exceeding the upper deformation limit and measurement signal noise caused at very low deformations. The stress is rapidly applied in an indirect tensile loading and maintained constant throughout the test. The creep compliance is then calculated based on the applied vertical load, time-dependent horizontal and vertical deformations, specimen dimensions, and gage length.

FIG. 1. Schematic diagram of the indirect tensile creep test.

Testing is usually conducted at three temperatures (0°C, -10°C, and -20°C; 32°F, 14°F, and -4°F) on samples that have a height of 38 to 50 mm (1.5 to 2 in.) The

standard ITC test is run for 100 seconds. During the test, the horizontal and vertical deformations are measured and then the creep compliance as a function of time can be determined as:

$$D(t) = \frac{\Delta X_t \times D \times b}{P \times GL} \times C_{cmpl} \quad (1)$$

where:

- D(t) creep compliance as a function of time
- ΔX_t mean of horizontal deformation as a function of time
- D specimen diameter
- b specimen thickness (height)
- P constant creep load
- GL specimen gage length
- C_{cmpl} Non-dimensional creep compliance factor

DEVELOPMENT OF ANN PREDICTION MODEL

ANN modeling is a relatively new technique that has emerged and is being recognized and used in many disciplines to model complex problems. Unlike other modeling techniques that rely on mathematical expressions to describe experimental observations, ANN relies on the learning capabilities of its elements. It was originally presented by Ghaboussi et al. (1990 and 1991).

The structure of an ANN consists of a large number of simple processing elements (units) called nodes or artificial neurons that are linked together in a way similar to the architecture of the human brain. A unique feature of ANNs is that these units learn from example in a manner similar to biological neurons (Fausett 1994). The information processing system is very attractive mainly due to its capability of learning, drawing parallelism and its ability to handle imprecise and fuzzy information. An ANN 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 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.

Design

There are many ways a neural network can be trained. The back propagation technique is retained in this study since it 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.

Using a subset of laboratory-determined creep compliance values used in the calibration of the thermal cracking performance model in the MEPDG (NCHRP 2003), an ANN investigation was undertaken to examine the effectiveness of the artificial neural network technique in predicting the creep compliance of novel asphalt concrete mixes and thus circumventing the need for laboratory testing. The laboratory data used in this study included experimental results of indirect tensile creep test performed on 30 mixes at three temperatures (-20°C, -10°C and 0°C). The laboratory database included creep compliance values of mixes covering a wide range of air voids (1.0% to 9.0%). These mixes also enveloped different binders with a wide range of high temperature (76 to 52) and low temperature (-22 to -34) performance grades and voids in the mineral aggregate (12.56% to 20.42%). The results of 20 mixes were used for training and the results of four mixes were randomly set aside and used for testing the trained network. The remaining six mixes (also randomly chosen) were reserved for comparing the predictions of the built network with laboratory obtained data (validation).

Realization

An ANN model consists of at least three layers. The first layer contains the input nodes, which represent the independent variables of the problem. The last layer contains the nodes representing the solution. A minimum of one hidden layer with a certain number of processing nodes is 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.

The realization of ANN models 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.

In this study, the creep compliance is the single targeted output. The inputs included five parameters, namely, binder performance grade, mix's air voids, voids in the mineral aggregates, temperature and time. 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 with varying number of hidden layers and nodes. 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:

$$|ARE| = \text{abs.} \{ (X_{\text{prediction}} - X_{\text{actual}}) / X_{\text{actual}} \} \times 100\% \quad (2)$$

Through trial-and-error it was found that using more than one hidden layer did not improve the accuracy of the predictions. Thus, 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 displayed in Figure 2. 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 15 nodes in the single hidden layer was found to provide the best accuracy with an $|ARE|$ of about 15%, which was considered acceptable since it was observed that replicate samples tested in the laboratory might exhibit an $|ARE|$ of up to 25%.

VERIFICATION OF THE DEVELOPED ANN MODEL

The ability of the ANN technique to predict the creep compliance in a satisfactory manner was determined by comparing ANN predictions and laboratory results of six 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 64-22, the air voids were 4.0 % and the voids in the mineral aggregate were 14.4% is presented in Figure 3. It shows that the ANN technique is capable of predicting the creep compliance in a satisfactory manner. ANN predictions mimicked the effect of temperature on the creep compliance observed in laboratory-testing of real asphalt concrete samples. Further, ANN predictions did not deviate substantially from laboratory measured values. The maximum $|ARE|$ was encountered with the predictions made at -10°C and 100 seconds where it reached about 27%. However, the $|ARE|$ was about 15% when the predictions and laboratory results at all temperatures and time were contrasted.

FIG. 2. Effect of number of nodes in the hidden layer on accuracy.

FIG. 3. ANN predictions vs. laboratory measurements.

CONCLUSIONS

The mechanistic-empirical pavement design guide requires the use of the creep compliance to characterize bituminous materials at low temperatures, which is used by the performance model to predict thermal cracking. However, the indirect tensile creep test dedicated to determine the creep compliance in the laboratory is time consuming. In addition, 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 presents the artificial neural network as an alternative to performing the test. 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 creep compliance of bituminous materials. Further, artificial neural network models were found to yield satisfactory accuracy; an absolute average relative error of about 15% was observed when the ANN predictions were compared to laboratory measurements.

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