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NEURAL NETWORK MODELING OF RESILIENT MODULUS AND PERMANENT DEFORMATION OF AGGREGATE MATERIALS

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Abstract

This paper presents the artificial neural networks (ANN) as a promising analytical technique that can provide pavement engineers with adequate databases that contain the resilient modulus and permanent deformation properties of aggregate materials. Utilizing a laboratory-generated data set, consisting of 30 test result entries, a number of ANN models were constructed and evaluated in this study. The laboratory database contained results that spanned a wide range of various factors that are known to influence the two mechanical parameters (resilient modulus, M_r, and percent permanent deformation, %PD) of the tested materials. The developed models showed good capabilities for estimating the two parameters at different states of stress, moisture contents, and percent fines passing sieve # 200 (0.075 mm mesh opening). The model that produced the least error in the value of the estimates was selected to expand the database to include conditions that were not covered in the laboratory study. Findings from this research clearly indicate the potential of ANN for expanding databases.

Introduction

The Urban Roads group of the National Research Council Canada has recently developed a new characterization scheme for determining the mechanistic properties of unbound materials (Khogali and Hussein, 2004). The established technique, named the M_r–PD test, goes beyond the conventional method of determining the resilient modulus (M_r) by concurrently measuring the percentage permanent deformation (%PD) that the material accumulates under dynamic loading. The two parameters obtained from the test define the full material response; thus making it an effective method for assessing the material's potential performance under prevailing in-situ conditions. Obtaining the two parameters in the laboratory for a wide range of physical and loading conditions is an expensive and time-consuming undertaking. This paper presents an approach that circumvents the need for extensive M_r–PD testing by combining the use of limited laboratory-generated data with analytical modeling to produce adequate size databases.

Artificial neural networks (ANN) are analytical techniques that mimic the process that the human brain uses to learn and make deductions. An ANN model consists of a number of neurons that are connected together in a way similar to the architecture of the human brain (Basheer and Hajmeer, 2000). These neurons, which reside in layers, are referred to as nodes. An ANN model is usually made up of three or more layers, with a specified number of nodes in each layer. The first layer contains the input parameters of the process that need to be modeled while the last layer contains the output (solution) parameter(s) of the process. One or more layers known as hidden layers are usually incorporated between the input and output layers. The number of hidden layers as well as the number of their nodes is usually determined by trial and error to achieve an optimum performance of the built network. The optimization process involves training the built network and testing it using a data set of known input and output entries.

There are many ways a neural network can be trained. The back propagation technique is one of the most popular processes and has been used in many fields of science and engineering such as construction simulation (Flood, 1990), constitutive modeling (Rogers, 1994) and structural analysis (Garrett et al., 1992). In a back propagation learning process, training is achieved by assigning random weights to the connections between neurons 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 inputs/outputs until the error obtained is within a certain tolerance. The resulting network with final connection weights is then saved to serve as the prediction model. The ANN model developed in this study utilized the back propagation process.

Model structure and adequacy

The ANN model developed in this study has four inputs, namely, percentage fines passing sieve #200 (0.075 mm), compaction density, moisture content and deviator stress that the material is subjected to. These factors were chosen because of their known effects on aggregate materials' behaviour (Hicks, 1970; Rada and Witczak, 1981; Smith and Nair, 1973; Sweere, 1990; Dawson et al., 1996; Khogali and Hussein, 2004). The model output included the two mechanistic parameters; the resilient modulus and the percentage permanent deformation. To arrive at an optimized network, several ANNs were developed and their prediction capabilities were assessed using the percentage "Absolute value of the Relative Error" (ARE) defined in Equation 1.

$$|ARE| = \frac{\left|\left(X_{predicted} - X_{Actual}\right)\right|}{\left|X_{Actual}\right|} 100\% \qquad (1)$$

The laboratory data used to build and train the ANN models consisted of 30 data sets, representing different conditions of density (89–98% Modified Proctor Density, MPD), moisture content (3.5–7%), deviator stress (35–80 kPa), and percentage fines (2–16%).

Initially, the search for an optimized model considered simple ANNs consisting of a single hidden layer. Results obtained indicated that regardless of the number of nodes used in the hidden layer, the developed models always gave good predictions of the %PD parameter (|ARE| < 15%) but not the M_r parameter (|ARE| > 35%). In a second stage of the analysis, the use of advanced models with two hidden layers was examined. Optimization during this stage involved varying the number of nodes in both hidden layers, considering one layer at a time. The use of eight nodes in the first hidden layer produced robust models that consistently exhibited |ARE| values that are lower than 25% for both outputs (M_r and %PD). Keeping the number of nodes to eight in the first hidden layer, the search for an optimum number of nodes in the second hidden layer yielded the pattern displayed in Figure 1. From this figure, it is evident that using seven nodes in the second hidden layer yielded satisfactory results with |ARE| less than 15% for the two output parameters. Accordingly, the final model selected for further evaluation and expansion of the database consisted of the one that contained two hidden layers with 8 and 7 nodes, respectively.

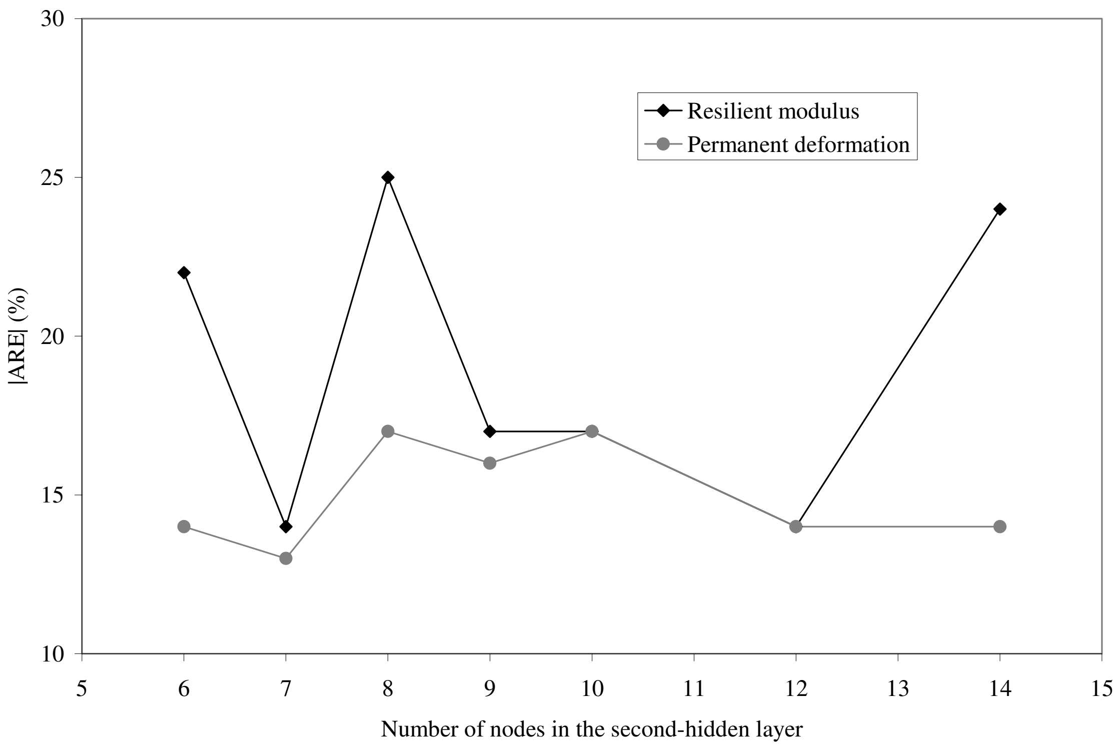

Figure 1. Effect of number of nodes in second hidden layer on model accuracy.

To ensure that the selected model had effectively learned the features contained in the original data set, the trained network was used to check known material behaviour related to variations in density, moisture content, percent fines, and deviator stress. Figure 2 shows typical predictions of M_r obtained at different stress levels for a material with 7% fines content compacted to 90% MPD and 4.0% moisture content. The displayed trend indicates an increase in M_r with an increase in stress. This effect diminishes at high stress levels (≥ 70 kPa), where the resilient modulus reaches a plateau. The results of Figure 2 clearly demonstrate the ability of the ANN model in capturing similar trends reported in the literature.

Figure 3 displays the combined effect of fines and moisture content on %PD. An increase in either moisture content or percent fines produces a corresponding increase in the amount of permanent deformation. Results shown are for a material compacted at 92% MPD tested at 50 kPa. The results depicted in Figure 3 concurred with laboratory observations. For a given percentage of fines, low moisture contents have little influence on permanent deformation. However, as the moisture content approaches the material optimum moisture content (5.5% for this example), the material starts accumulating permanent deformation at a high rate. As the moisture content is increased further beyond the optimum, a decrease in the rate of accumulation of permanent deformations is observed. It is also noted that the effect of fines content on permanent deformation is quite significant (e.g., the predicted %PD at 5.5% moisture for a material with 5% fines content is 0.67% compared with a %PD of 2% for a material with 12% fines content).

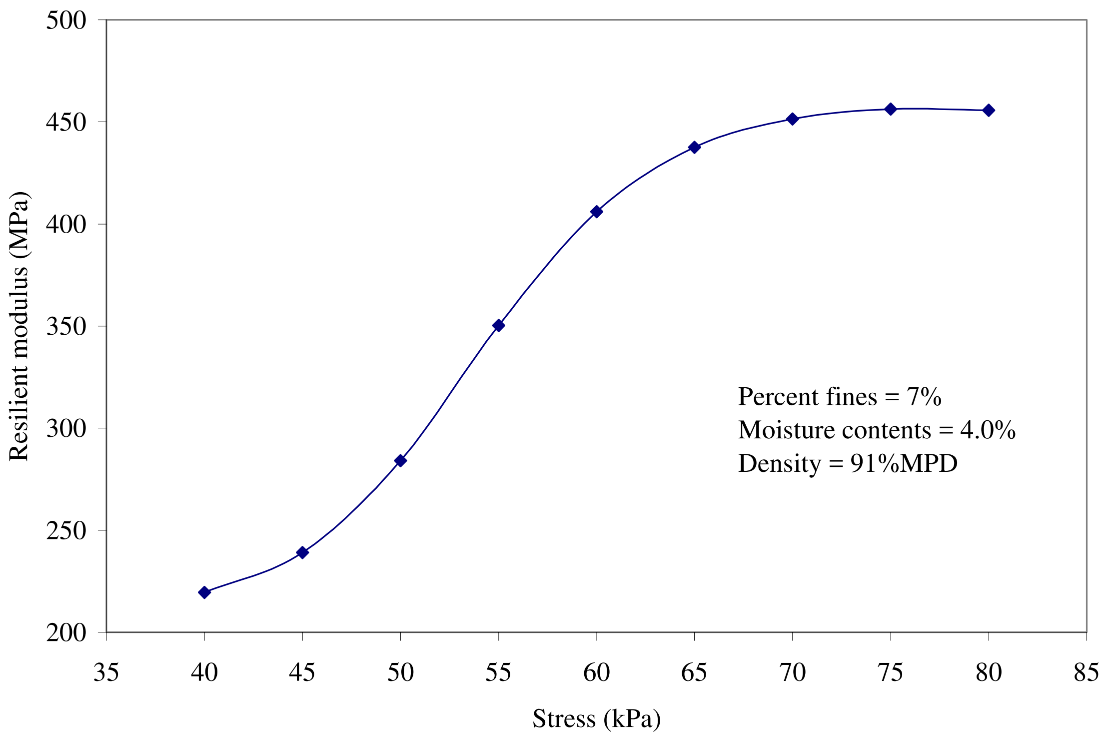

Figure 2. Effect of deviator stress on resilient modulus.

Population of database

After assessing its adequacy, the ANN model was utilized to populate the original laboratory database. The process involved selecting specific increments within each range of the four input parameters and using the ANN model to predict values of the two outputs (M_r and %PD) at various combinations of the selected increments. This exercise resulted in expanding the original database from 30 to more than 10,000 data entries covering the ranges of input variables in increments of 1% for compaction density, 0.5% for moisture content, 1% for percent fines, and 5 kPa for deviator stress. An example illustrating the population of the database for a typical aggregate material containing 7% fines and compacted to a typical road specification of 95% MPD is given in Table 1. The example depicted in Table 1 covers the full range of moisture content (3.5–7%) and only two stress levels (40 and 80 kPa).

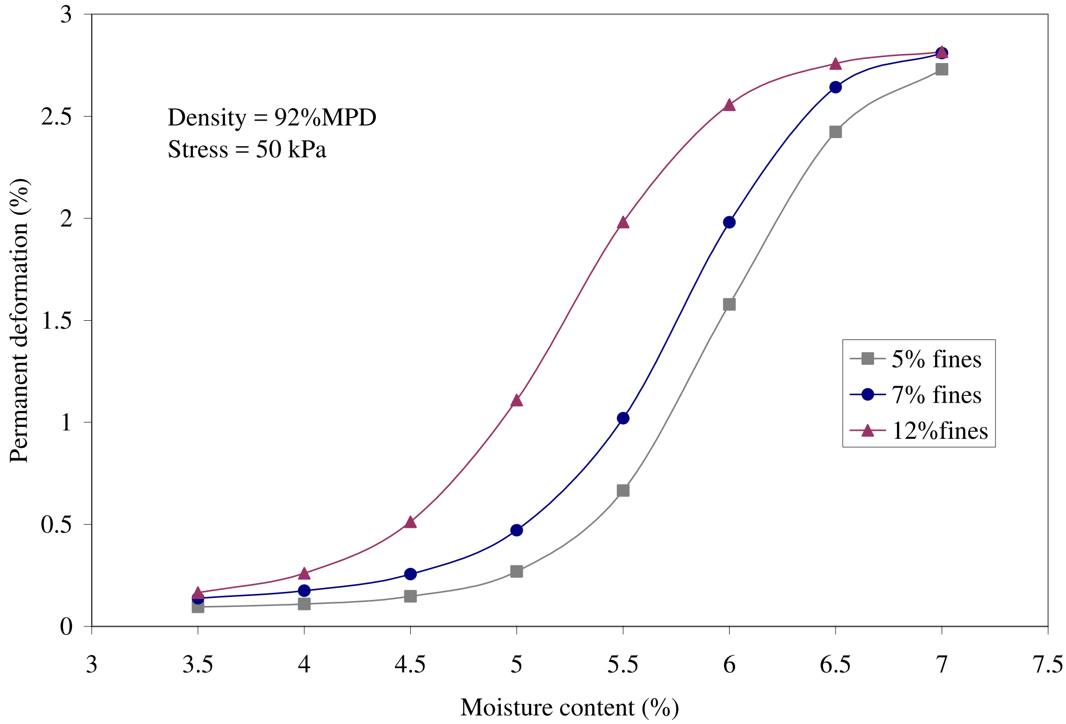

Figure 3. Combined effect of fines and moisture content on permanent deformation.

Deviator stress (kPa)	Moisture content (%)	Resilient modulus (MPa)	Permanent deformation (%)
40	3.5	151	0.10
	4	142	0.12
	4.5	134	0.16
	5	124	0.27
	5.5	110	0.64
	6	92	1.50
	6.5	74	2.35
	7	60	2.70
80	3.5	353	0.23
	4	318	0.40
	4.5	273	0.78
	5	222	1.39
	5.5	176	2.00
	6	142	2.39
	6.5	119	2.61
	7	103	2.72

Table 1. Example showing population of database.

Conclusions

An analytical study was carried out to examine the merits of using the artificial neural network (ANN) technique to alleviate the need for extensive testing to characterize aggregate materials. A small laboratory-generated data set, covering a wide spectrum of factors that are known to influence the materials' resilient and permanent deformation properties, was used to build and train the ANN model. Results obtained showed that the ANN technique is a powerful tool that has the capability of capturing material behaviour trends observed in the laboratory and reported in the literature. Furthermore, the developed model exhibited satisfactory accuracy (≤ 15% Absolute Relative Error) in providing estimates of the resilient modulus and percentage permanent deformation. The tool was effectively utilized to expand the original database from 30 entries to more than 10,000 entries.

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