Turkish J. Eng. Env. Sci.
26 (2002) , 243 – 248.

Artificial Neural Network Application for Flexible Pavement Thickness Modeling

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Received 02.10.2000

Abstract

Flexible pavements are affected by moving vehicles, climate and other environmental factors. As a result of these factors, the pavement starts to deteriorate. In order to prevent further deterioration, a maintenance program should be carried out at right time and right places. For the determination of the structural carrying capacity of the pavement, non-destructive testing equipments are used. These are mainly Benkelman Beam, dynaflect, road rater and falling weight deflectometer (FWD). In such a process, the most important thing is to analyze the collected data. A backcalculation procedure is carried out for back-calculating the elastic modulus for each layer that has an effect on the pavement life. Generally, linear elastic and finite element based programs are used for backcalculation, but they are time consuming. An artificial neural network (ANN) approach is used for the elimination of this drawback during the course of this study. Results indicate that the ANN can be used for backcalculation of the thickness of layers with great improvement and accuracy.

Key words: Backcalculation, Elastic modulus, Neural networks, Flexible pavements

Introduction

Highway pavements are generally constructed in the form of flexible materials in which there are an asphaltic concrete wearing course on the top, and base and sub-base layers underneath the wearing course. The base material may be a bituminous mix or granular material depending on the passage number of heavy vehicles from the considered section of the road. However, the sub-base layer is generally built with granular material obtained from local quarries. Repeated application of vehicle loads, weather conditions and other factors decrease the serviceability of the pavement. In other words, the comfort decreases while the user costs and the operation cost increase. For this reason, a maintenance program should be set up to decide when and where to carry out maintenance work. It is important that the maintenance activities be done at the right time and right places.

Perhaps the most difficult factor to determine is the remaining life of the pavement. Many distresses can be seen by eye. In order to determine the remaining life, the pavement should be analysed structurally with material properties for each layer in terms of elastic modulus, Poisson's ratio and thickness of layers. In order to determine the thickness, geophysical methods or drilling can be used. Furthermore, for determining the structural capacity of the pavement, non-destructive test (NDT) methods are used generally. These are mainly Benkelman beam, road rater, dynaflect and falling weight deflectometer (FWD). Since the FWD simulates the wheel loading and its dynamic feature, many countries use the FWD (see Figure 1).

Deflections obtained from the FWD are used to backcalculate the layer material properties, which are elastic modulus, Poisson's ratio and layer thicknesses. In order to determine the material proper-

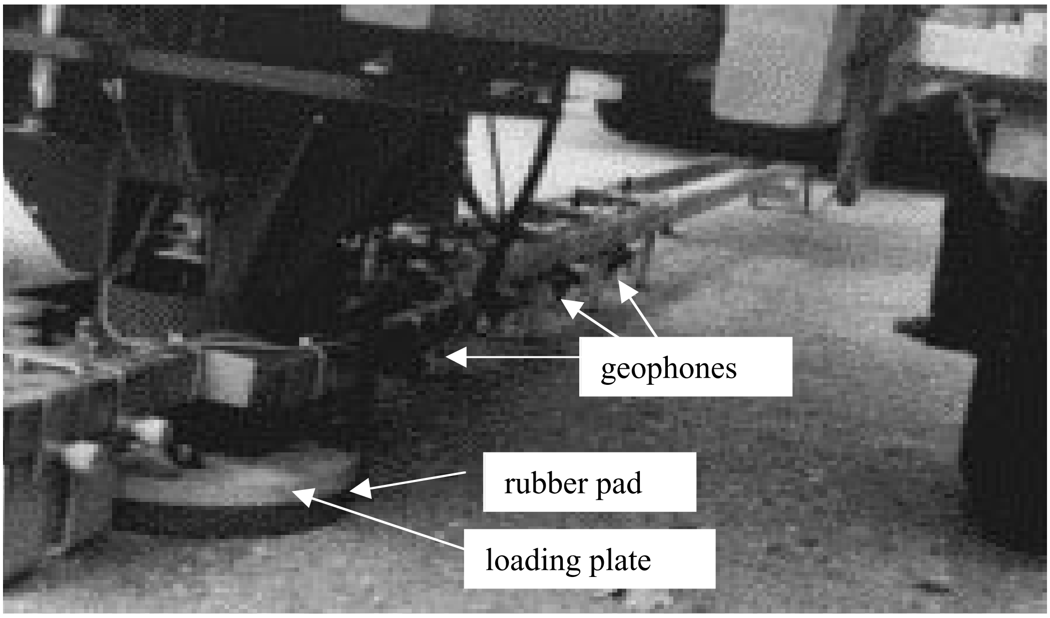

Figure 1. FWD loading and measurement system

ties, linear elastic theories and finite element methods (FEM) are used. However, an artificial neural network (ANN) can also be used to backcalculate material properties.

The Nature of FWD Testing

In order to simulate the truck loading on the pavement, a circular plate is dropped on the pavement from a certain height. The height is adjusted according to the desired load level. Underneath the circular plate a rubber pad is mounted to prevent shock loading. Seven geophones are generally mounted on the trailer (the number of geophones may vary). When the vertical load is applied on the pavement, the geophones collect the data in byte form. Using the calibration factors, the bytes can be converted to the real deflections.

Benkelman beam and dynaflect, which are mostly used in the developing countries, only give information about the pavement underneath the circular plate. In the meantime, the FWD gives information about six other points, which are away from the circular plate. Therefore, the effect of the wheel loading can also be seen at other points.

There are many types of FWDs that can apply the same loading. The frequencies of loading vary between 0.025 and 0.030 sec; the applied loads vary between 6.7 and 156 kN. The loads are generally applied in a sinusoidal form (Stolle, 1991; Stolle and Jung, 1991). The loading time of 0.030 represents the wheel loading moving at a speed of 30 km/h and mm deviations up to ± 0.023 can be seen in the FWD measurements (Shaat and Kamal, 1991).

Interpretation of FWD Measurements

A typical deflection bowl obtained from the FWD loading is shown in Figure 2. It is obvious that underneath the circular plate, the maximum deflection is obtained. However, points away from the circular load application point have smaller deflections.

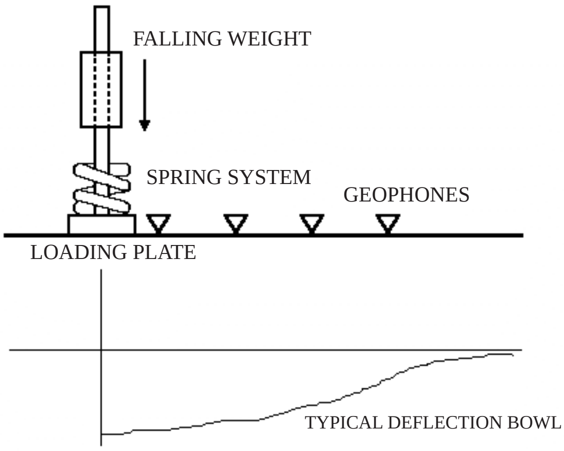

Figure 2. Typical deflection bowl obtained from a FWD loading

When we apply the FWD loading, the load and the deflections due to the FWD loading are both known. However, for the structural analysis, the layer materials should be known. There are two unknowns in the problem: the elastic modulus and Poisson's ratio of each layer. Sometimes, there is no information about layer thickness. Generally, the effect of Poisson's ratio is ignored in the pavement analysis; therefore, constant Poisson's ratios are generally assigned to each layer. For these purposes, some computer programs are written which use linear elastic theory and finite element methods. In the linear elastic theory, all materials in the pavement are assumed to behave linearly, which is not a valid assumption for the pavement materials. Especially, granular materials and soils behave in a nonlinear manner. Apart from this, there is constraint in width along the road, which is again not a valid assumption. Therefore, in recent years finite element methods have been considered to overcome the above problems. One of the finite element programs is written by the first author of this paper (Saltan, 1999). The problem in using the finite element programs is to prepare meshes for each problem which is time consuming. Apart from this, an iteration approach should be used to find the solution, which is again time consuming.

For the backcalculation analysis, an initial elastic modulus is set up for each layer. The FWD loading is then applied on the mesh vertically and deflections are compared with error functions below. If the error is not in the acceptable range, the elastic modulus has to be changed until the error function is satisfied. Following the satisfaction, the elastic modulus for each layer is assumed as known quantities. Hence, a forward analysis is carried out with the obtained values in order to find the tensile strain underneath the bituminous mixture and vertical strain on the subgrade. Results obtained from the forward analysis are entered into the fatigue and plastic deformation graphics. From these two graphics, the remaining life of the pavement is then determined. Finally, a decision is made as to whether the overlay is necessary or not. For an objective decision, the following relative error square summation, *RSS*, is generally employed.

For the study the following objective function was chosen:

$$\sum_{i=1}^{s}\left(d_i^m - d_i^h\right)^2 < \varepsilon \tag{1}$$

where d_i^h = calculated deflections in ith geophone; d_i^m =measured deflections in ith geophone; s= sensor number from i to s, and ε is a constant that depends on the accuracy.

Artificial Neural Networks

Artificial neural networks (ANNs) are widely used in a variety of practical tasks from process monitoring, fall diagnosis and adaptive human interference to natural events and artificial intelligence such as computers (Dimitrova, 1996). They are very important in control system applications because of their universal mapping characteristics and learning ability. An ANN process can be considered black-box modelling with a set of input factors and output variables which are a result of input factors treatment through a systematic neural network. The first appearance of the ANN concept in the literature is due to McCullough and Pits (1943), who suggested the cell model. In such a model, ANNs are exemplified as a set of logical statements. Later on, many researchers concentrated their attention on the learning ability of humans and its modelling (Hebb, 1949), which can be considered the pioneering work on ANNs. However, actual leaps in ANN development appeared towards 1980 through various studies (Hopfield, 1982).

Initially, an ANN can be divided into two parts: architecture and neurodynamics (functional properties). The former defines the structure of the network as the number of artificial neurons and their interconnectivity, whereas the latter includes their properties as to how the neural network learns, recalls, associates and continuously compares new information with existing knowledge, and how it classifies new information and the development of new classifications if necessary. ANN architecture includes many interconnected neurons or processing elements with familiar characteristics such as inputs, synaptic strengths, activation, output and bias (Sönmez and Şen, 1998).

In general, a neuron has n inputs as x_j, ($j=1,2,\ldots,n$), which show the source of input signal. Each input is weighted before reaching the main body of the processing element (artificial neuron) by the connecting strength or the weight factors, w_j. Hence, the signal transferred through the connection strength is equal to a portion of the original signal as $w_j x_j$. On the other hand, for the neuron to produce a signal, the input signal to a neuron must exceed a threshold value, T, and in addition it has, in general, a bias term B. After the effects of the bias and the threshold on the weighted signal a nonlinearity function, F, i.e. activation R, enters this nonlinear unit and then comes out as completely treated output, O. Of course, this output may be an input for some other neurons. If there are many neurons in a network, then each neuron is called a node within the network. If there are m nodes in a network then the above-mentioned procedures will work for each one of them. In order to distinguish between neurons the subscript i will be used. Accordingly, inputs, weights, activation signals, outputs, threshold and nonlinear function will all have identification subscript, i. The transfer function in an ANN is given by the following relation:

$$O_i = F_i \left(\sum_{j=1}^{n} w_{ij} x_{ij} \right) \qquad (2)$$

with the neuron's firing condition as

$$\sum_{i=1}^{n} w_{ij} x_{ij} \geq T_i \qquad (3)$$

where the subscripts i and j represent the neuron in question and the inputs from the neurons.

The reason for including the nonlinearity function is to ensure the neuron's bounded response. This means that the actual response of the neuron is conditioned or damped as a result of large or small activating stimuli and thus is controllable. It is well known that in order to hear a sound twice as loud, an actual increase in sound amplitude of about 10 times is necessary. This shows the almost logarithmic response of the ear.

Two of the most used nonlinearities are the hard limiter and the sigmoid (as expressed in Equation 3), where x is the variable and $F(x)$ is the activation function. Most of the limiters have upper and lower limits of ± 1, or 0 and 1. In an actual ANN application, it is up to the user to choose the bound values. However, the sigmoid is very popular because it is bounded, monotonic and nonlinear, and has a simple derivative.

$$F\left(\Sigma w_{ij} x_{ij}\right) = \frac{1}{1 + e^{-(\Sigma w x)}} \qquad (4)$$

Threshold values in equations are assumed to be zero in order to take into account even smaller weights in the network. Therefore, a better approximation to the problem solution can be obtained.

Artificial Neural Networks in Backcalculating Pavement Layer Thickness

Setting the finite element mesh and iteration procedure of backcalculation takes rather a long time. The ANN procedure will reduce the required computation significantly.

In order to develop an ANN based backcalculation procedure, it is necessary first of all to have a data base. For this reason a forward analysis is carried out for each value of elastic modulus, Poisson's ratio and thickness. For this purpose, a computer program, KENLAYER (Huang, 1993), was used. A typical flexible pavement in which wearing course, base and sub-base layers exist was chosen (see Figure 3). For simplicity, base layer thickness is assumed to be constant, whereas wearing course layer thickness varies. The elastic modulus for the asphalt concrete is between 1000 and 4000 MPa. For the base layer and subgrade, the elastic moduli are assumed to be 500 and 100 Mpa. Poisson ratios for asphalt concrete, base and subgrade are chosen as 0.30, 0.40 and 0.45, respectively. For each run, seven deflections, which are 0.305 m apart from each other, elastic modulus, Poisson's ratio and thickness are saved in a file. Seventy-five structural analyses were carried out in order to obtain deflections using the KENLAYER program.

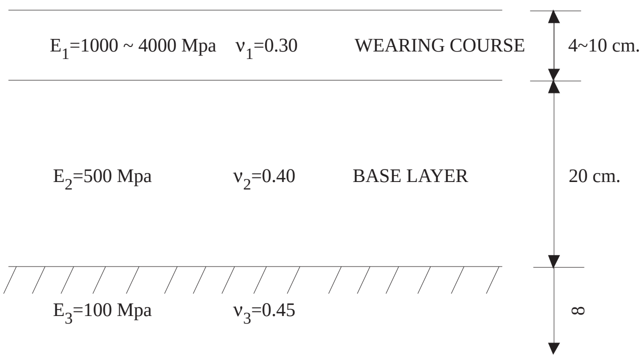

Figure 3. A typical flexible pavement used in the analysis

In order to develop a backcalculation procedure using the ANN, the deflection bowl is assumed to be known, whereas elastic modulus, Poisson's ratio and layer thickness are unknown. Such an approach is just the opposite of the forward analysis. For the study in this paper, a multilayer ANN architecture was chosen, as seen in Figure 4. A backpropagation learning algorithm was employed for learning in the MATLAB program (Hanselman and Littlefield, 1996). The number of hidden layers is varied as 2, 4, 8, 16 and 32 in order to see the sensitivity of the results. The number of neurons in the hidden layer affects highly the sum squares of error (see Table 1). The neuron number in the hidden layer is considered to be 32, which yields the smallest sum of squares of error.

In Figure 4, seven deflection values were employed in the input layer, and asphaltic concrete elastic modulus as well as the thickness of bituminous mixture were represented in the output layer. The network was then trained using 52 run results. For the training process, 200,000 epoches were carried out, and the sum of square errors is equal to 0.003. The training results are shown in Figure 5. The training network for layer thickness gave a quite close approximation to the observed values. A regression analysis was carried out to see the approximation between the observed and calculated layer thickness, as shown in Figure 6. The regression coefficient is 0.944 for the thickness, which is acceptable for the highway industry. Furthermore, 23 data sets, which were considered previously in the training process, were used to test the trained network. The results are shown in Figures 7 and 8. For the test data sets, the regression coefficient is 0.884 for the thickness. These results indicate that the ANN can be effectively used to determine the layer thickness.

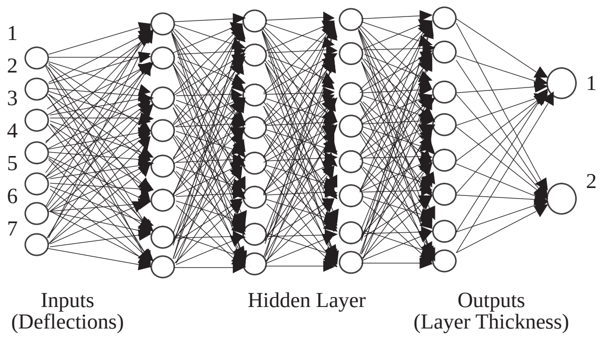

Figure 4. The ANN architecture

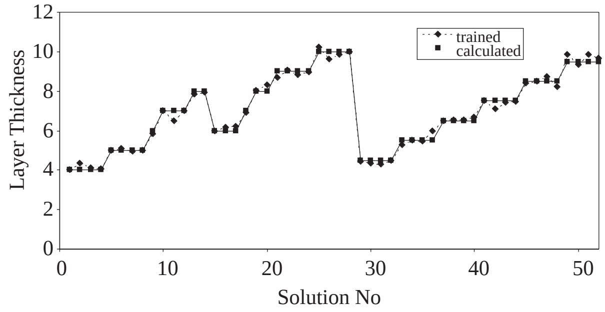

Figure 5. Calculated and trained layer thickness (cm)

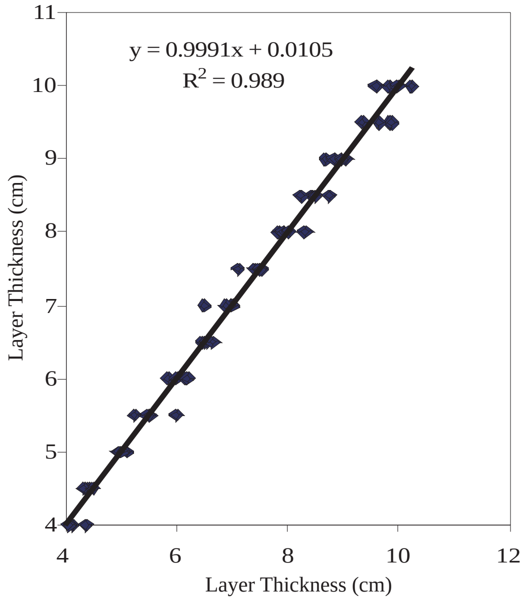

Figure 6. Scatter diagram of actual and trained values for layer thickness

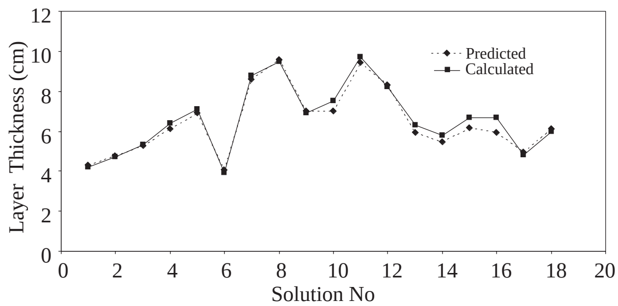

Figure 7. Calculated and predicted layer thickness

Table 1. The Sum Squares of Error for Neuron Number in Hidden Layer

Neurons of Hidden Layer	2	4	8	16	32
Sum Squares of Error	0.1784	0.0907	0.0402	0.0212	0.0126

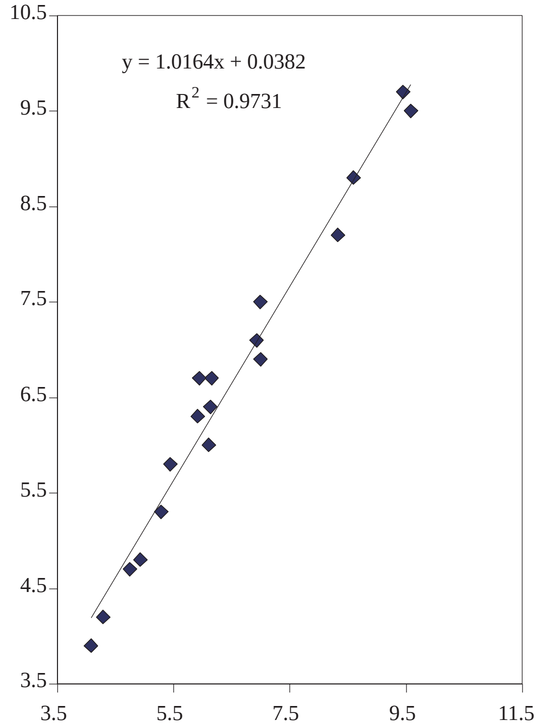

Figure 8. Scatter diagram of calculated and predicted values for layer thickness

Conclusions

The backcalculation procedure for flexible pavements is time consuming and expensive. In such a procedure, deflections and thickness are assumed to be known. However, determination of pavement layer thickness is time consuming and expensive. Therefore, using the ANN approach, the thickness of each layer can be determined with a small amount of error and geophysical methods or drilling might not be used. Using a package program for backcalculation, especially finite element programs, needs mesh generation, which takes relatively longer. With an ANN it is possible to obtain results with 10-15% error, which may be better than with many package programs.

Acknowledgment

The authors would like to thank Sakarya University Industrial Engineering Lab for making the MATLAB software available for the paper preparation.

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