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Kenlayer Based Pavement Backcalculation Moduli Using Artificial Neural Networks

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Abstract: In the mechanistic flexible pavement design procedure, the resilient moduli of the individual pavement layers must be known prior to the computation of critical pavement responses. The use of Falling Weight Deflectometer (FWD) data to backcalculate pavement layer moduli is a cost-effective and widely used method. Most of the commercial backcalculation programs do not account for the nonlinearity of unbound granular materials and fine-grained cohesive soils and therefore often do not produce realistic results. Kenlayer is structural pavement analysis software which incorporates with nonlinearity, stress dependent resilient modulus material models, and failure criteria for the materials of the pavement's layers. Multilayer perceptron networks which use an error-backpropagation learning algorithm were trained to approximate the FWD backcalculation function. The genetic algorithm was used to identify the best topology for the networks. The study showed that by using neural networks with proper topologies the coefficient of determination (R^2), in estimating K_{base} and E_{as} was increased to 0.85 and 0.97. Therefore neural networks can be used as a fast and accurate tool for backcalculating pavement layer moduli.

Key words: *Artificial neural networks; Backcalculation; Falling weight deflectometer; Non-destructive testing.*

Introduction

A conventional asphalt concrete pavement is typically made up of three layers which are surface layer paved with asphalt concrete mix, base or/and subbase layer made up of crushed stone, and subgrade layer made up of natural soil. The deflection of the pavement represents an overall "system response" of the pavement layers to an applied load. When a load is applied on a flexible pavement, the pavement layers are deflected nearly vertically to form the basin called deflection basin. The deflected shape of the basin is a function predominantly by the thickness of the pavement layers, the moduli of the individual layers, and the magnitude of the load. The Falling Weight Deflectometer (FWD) test is one of the most widely used tests for assessing the structural integrity of roads in a non-destructive manner [1]. In a FWD test, an impulse load is applied to the pavement surface by dropping a weight onto a circular metal plate and the resultant pavement surface deflections are measured directly beneath the plate and at several radial offsets. The FWD test aims to simulate the force history and deflection magnitudes of a moving truck tire.

Backcalculation generally refers to an iterative procedure whereby the layer properties of the pavement model are adjusted until the computed deflections under a given load agree with the corresponding measured values [2].

It is well known that granular materials and subgrade soils are nonlinear with an elastic modulus varying with the level of stresses [3]. The elastic modulus used for the layered systems is the resilient modulus obtained from repeated unconfined or triaxial compression tests.

Unbound granular materials used in the base/subbase layer of a flexible pavement show "stress-hardening" behavior (increase in resilient modulus with increasing hydrostatic stress), and cohesive subgrade soils show "stress-softening" behavior (reduction in resilient modulus with increasing deviator stress) [3].

Therefore, the layer modulus is no longer a constant value, but a function of the stress state. The pavement layer moduli values predicted using the backcalculation programs which assume the linear elastic behavior for the materials of pavement are not very accurate.

The Kenlayer computer program can be only applied to flexible pavements with no joints or rigid layers [4]. The backbone of Kenlayer is the solution for an elastic multilayer system under a circular loaded area. The solutions are superimposed for multiple wheels, applied iteratively for nonlinear layers, and collocated at various times for viscoelastic layers. As a result, Kenlayer can be applied to layered systems under single, dual, dual-tandem, or dual-tridem wheels with each layer behaving differently, either linear elastic, nonlinear elastic, or viscoelastic [4].

The goal of this research was to develop a tool for back-calculating nonlinear pavement layer moduli from FWD data using Artificial Neural Networks (ANNs). The reason for using ANNs to accomplish this task was that they could learn a backcalculation function that was based on much more realistic models of pavement response (e.g. Kenlayer) than those used in traditional basin matching programs. ANNs have been successfully used in the past for the backcalculation of flexible pavement moduli from FWD data [5].

Kenlayer was used in this study to develop the synthetic data patterns which accounts for nonlinearity in unbound material behaviour. Multilayer feedforward perceptron networks which use an error-backpropagation learning algorithm, were trained to approximate the FWD backcalculation function.

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Neural Network Data Patterns Preparation

Three types of data patterns were generated using Kenlayer to train, cross validate, and test the neural network. A conventional flexible pavement section was modeled as a three-layered (asphalt layer, base layer, and subgrade layer), axisymmetric structure. In running Kenlayer, the granular base was divided into seven layers with the stress points shown in Fig. 1.

For analyzing deflection basins, average layer moduli based on RCNOL[1] = 7.6cm and SLD[2] = 0.25 is recommended. The stress point for the subgrade was assumed at depth of 60cm [4].

By using different asphalt moduli, and K for base and subgrade and also changing the thickness of asphalt and base, the deflections of pavement under FWD loading at radial distances from loading plate can be calculated. Comparison of deflection basins by different models are shown in Fig. 2. This figure shows that by choosing proper asphalt moduli and K for base and subgrade and also by choosing proper stress points, Kenlayer can simulate the deflection basin of the field and match with the field measurements accurate enough [4].

After values of K for both the granular base and subgrade are backcalculated from deflection measurements, they can be used to determine the maximum tensile strain at bottom of asphalt layer and maximum compressive strain on top of subgrade layer by selecting the stress points directly under the load. This is the major advantage of nonlinear analysis over the linear analysis. In the linear analysis, the backcalculated moduli are used directly for design, regardless of the fact that the layer moduli is not uniform and varies with the magnitude of the load and the distance from the load. In the nonlinear analysis, values of K based on the matching of deflection basin, are backcalculated and later used to determine the moduli based on the magnitude of load and the location at which responses are to be evaluated [4].

A typical FWD test is performed by dropping a 4,100kg load on top of a circular plate with a diameter of 30.4cm resting on the surface of pavement. Deflections are measured at offsets of 0, 30, 60, 90, 120, 150, and 180cm from the load center of loading plate.

Since the time of loading in FWD test is so short, asphalt layer was modeled as linear elastic material. For granular base, a relationship between resilient modulus and the first stress invariant can be expressed as following [3]:

$$E = K_{base}\theta^{K_2} \tag{1}$$

where E is the resilient modulus (MPa), θ is the first invariant stress, which can be either the sum of three normal stresses or the sum of three principal stresses. K_{base} and K_2 are obtained from laboratory repeated load triaxial test.

Although this model has been questioned by a number of researchers [6], it is the most widely used model [7].

Based on extensive testing on granular materials, the following relationship between K_{base} and K_2 has been proposed [8]:

[1] Radial Coordinate on pavement surface for computing elastic modulus of Nonlinear Layer

[2] Slope of Load Distribution

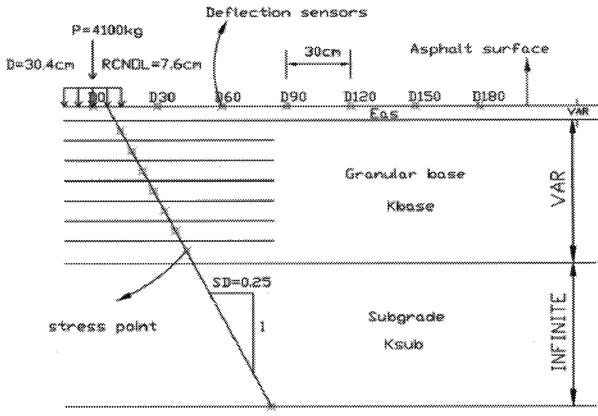

Fig. 1. Cross Section of Pavement for Deflection Analysis.

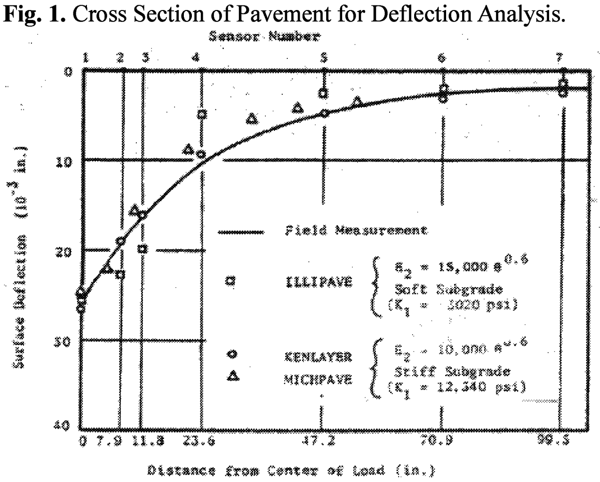

Fig. 2. Comparison of Deflection Basins in Different Models [4].

$$Log_{10}(K_{base}) = 4.657 - 1.807K_2 \qquad (R^2 = 0.68) \tag{2}$$

Accordingly, good quality granular materials, such as crushed stone, show higher K_{base} and lower K_2 values, whereas the opposite applies for lower quality aggregates.

The resilient modulus of fine-grained soils decreases with increase in deviator stress. The bilinear behavior can be expressed as following [9]:

$$\begin{aligned} E &= K_{sub} + K_3(K_s - \sigma_d) \quad \text{where } \sigma_d \le K_s \\ E &= K_{sub} - K_4(\sigma_d - K_s) \quad \text{where } \sigma_d \ge K_s \end{aligned} \tag{3}$$

in which K_{sub}, K_s, K_3, and K_4 are material constants and σ_d is the deviator stress.

The value of resilient modulus at the breakpoint in the bilinear curve is a good indicator of resilient behavior, while other constants such as K_s, K_3, and K_4 display less variability and influence pavement response to a smaller degree than K_{sub} [4]. Fine-graine soils has been categorized into four types, which are very soft, soft, medium, and stiff, with the resilient modulus-deviator stress curve shown in Fig. 3.

In this research, the 7 deflections which were computed at radial offset values, the thickness of asphalt surface layer, and the thickness of base layer together form the 9 input parameters for the neural network. The natural subgrade was assumed to be of infinite thickness and the thickness was not considered. The modulus of the

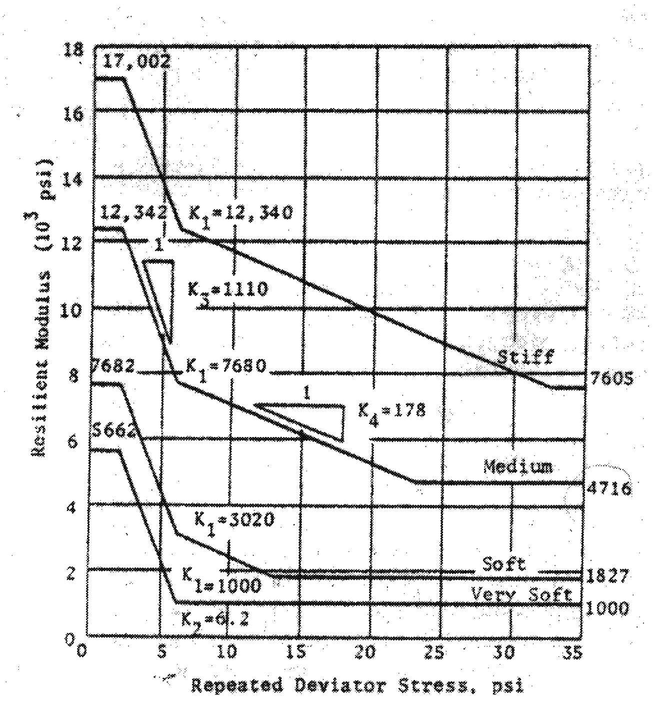

Fig.3. Resilient Modulus-Deviator Stress Relationship for Four Types of Subgrades [10]. (Note $K_1 = K_{sub}$ and $K_2 = K_s$ in this figure)

asphalt layer (E_{as}), the modulus of the base layer (K_{base}), and the modulus of subgrade layer K_{sub}, represent the 3 output parameters.

A total of 7,200 data patterns were generated by varying pavement layer thicknesses and moduli values. 5,200 data patterns were used to train the ANN, 1,300 data patterns were used to cross validate, and 700 data patterns were used to test the trained network.

The K_{sub} parameter and also the upper and lower limits for the modulus of the subgrade should be introduced to Kenlayer as inputs. The following equations can be extracted from Fig. 3 for determining the upper and lower limits for the subgrade's modulus:

$$\begin{aligned} E_{\max}sub[KPa] &= 32167.8 + K_{sub}[KPa] \\ E_{\min}sub[KPa] &= 11040 + 2.76K_{sub}[KPa] \end{aligned} \quad (4)$$

The pavement geometry and material property/model inputs for Kenlayer solutions are shown in Table 1.

Artificial Neural Networks

A neural network is an adaptable system that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data. Some networks are supervised, in that a human must determine what the network should learn from the data. Other networks are unsupervised, in that the way they organize information is hard-coded into their architecture [11].

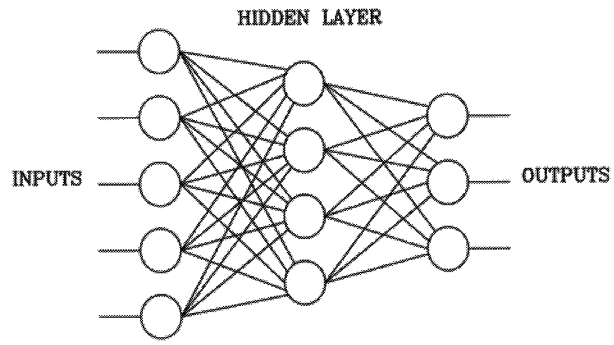

Fig. 4. Feedforward Artificial Neural Network.

In feedforward architecture networks information flows from the input layer to the hidden layer and then to the output layer. A typical example of such networks is shown in Fig. 4. Signals only go forward through the network with no loop backs [12].

Artificial Neural Network Training and Topology Optimization

A multilayer perceptron artificial neural network was trained in this study with the results which were obtained by Kenlayer and was used as rapid analysis design tool for backcalculation in flexible pavements. To train the network the backpropagation learning algorithm was used. Backpropagation learning algorithm is often used in conjunction with feedforward networks and it provides a way of using examples of a target function to find the weights that make the mapping function approximate the target function as closely as possible [13]. The method usually used to calculate the weight changes is the gradient descent. A series of iterations is done in which the calculated output is compared with the known values, adjusting the weights in such a way that the difference between the calculated values and the target function is minimized. For each of iteration, there is thus a forward pass followed by a backward pass during which error information is propagated backward from the output neurons to the hidden neurons [14]

Four networks, with 1, 2, 3, and 4 hidden layers with initial number of neurons in each hidden layer were constructed and optimized using Genetic Algorithms (GAs). GAs are general purpose search algorithms based upon the principles of evolution observed in nature. GAs combine selection, crossover, and mutation operators with the goal of finding the best solution to a problem [15].

Table 1. Pavement Geometry and Material Property/Model Inputs for Kenlayer Solutions.

Material type	Layer thickness	Material model	Layer modulus inputs
Asphalt concrete	50 to 250mm	Linear elastic	E_{as} = 800 to 11,200MPa
Granular base	120 to 400mm	Nonlinear elastic	K_{base}= *20 to 80MPa* K_2 = 0.32 to 0.66
Fine grained subgrade	Infinite	Nonlinear elastic	K_{sub} = 10 to 85MPa E_{max} = 42 to 117MPa E_{min} = 10 to 45MPa

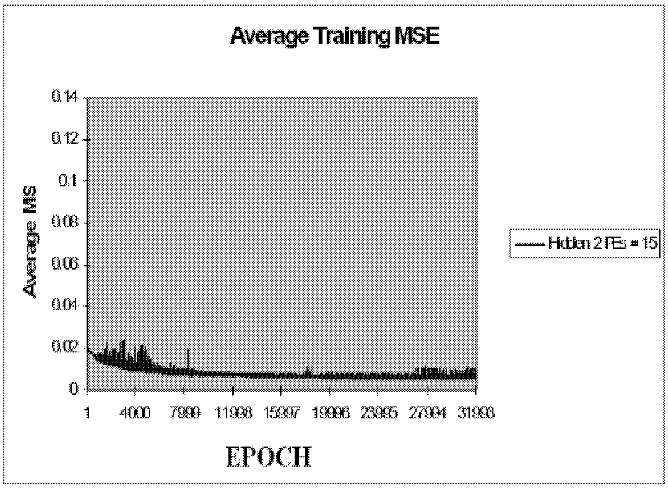

Fig. 5. Training Curve for the 9-24-15-3 Network.

Two hidden layer network topology was found to be sufficient in solving a problem in this size. The best topology which had the most linear correlation coefficient and the least mean squared error was found to be 9-24-15-3. It means that the network had 9 inputs, which were 7 deflections, the thickness of asphalt layer, and the thickness of base layer, two hidden layers with 24 and 15 neurons, and 3 outputs which were E_{as}, K_{base}, and K_{sub}. The transfer function in the hidden layers was hyperbolic tangent and in the output layer was linear sigmoid.

Using the Kenlayer synthetic data patterns, the ANN with the best topology was trained to learn the relationship between the synthetic deflection basins and thicknesses (inputs), and the pavement layer moduli (outputs). To monitor the performance of the network a mean squared error at the end of each epoch was calculated. An epoch is defined as one full presentation of all the training sets to the network. Cross validation which is a highly recommended method for stopping training has been used in this study [11]. This method monitors the error on an independent set of data and stops training when this error begins to increase. This is considered to be the point of best generalization [11].

The training curve and mean squared error values are presented in Fig. 5 and Table 2. Table 2 shows that at epoch number 36,209 the cross validation error was at its minimum and at epoch number 39,844 the training error was at its minimum. It means that although the network was trained for 39,844 epochs but from epoch number 36,209 to 39,844 the cross validation error did not further decrease. Therefore the best weights which lead to the best network generalization were obtained and saved at epoch number 36,209.

Discussions

The performance of the network to generalize to test data patterns can be evaluated with three parameters which are R, MSE, and $NMSE$. These parameters are calculated using the following formulas [11]:

$$MSE = \frac{\sum_{i=0}^{N}(D_i - Y_i)^2}{N} \tag{5}$$

$$NMSE = \frac{N^2 \times MSE}{N\sum_{i=0}^{N} D_i^2 - (\sum_{i=0}^{N} D_i)^2} \tag{6}$$

$$R = \frac{\sum (D_i - \overline{D})(Y_i - \overline{Y})}{[\sum (D_i - \overline{D})^2 \sum (Y_i - \overline{Y})^2]^{0.5}} \tag{7}$$

in which:

N = number of exemplars in the test data patterns,
D_i = desired output for exemplar i,
Y_i = network output for exemplar i,
$\overline{D}$ = mean of the desired outputs,
$\overline{Y}$ = mean of the network outputs,
MSE = Mean squared error,
$NMSE$ = Normalized mean squared error,
R = Linear correlation coefficient.

The performance of the 9-24-15-3 network to predict the test data patterns is shown in Table 3.

Figs. 6, 7, and 8 show the performance of the 9-24-15-3 network and display the target and ANN predicted moduli of the asphalt, subgrade, and base layers, respectively for the 700 test data patterns. The coefficient of determination values (R^2) are reported in the scatter plots.

Table 3 and Fig. 8 show that the base layer modulus was the hardest to predict. The difficulty associated with backcalculating the base layer modulus is a well recognized problem [16]. In order to improve the efficiency of neural network prediction capability, another network with the 11-25-6-1 topology was designed and trained with the same data patterns as the 9-24-15-3 network. In this

Table 2. *MSE* Values for Training and Cross Validation Data Patterns for the 9-24-15-3 Network.

Best Networks	Training	Cross Validation
Hidden 2 PEs	15	15
Run #	1	1
Epoch #	39,844	36,209
Minimum *MSE*	0.004863308	0.006557632
Final *MSE*	0.004863308	0.006908725

Table 3. The performance of the 9-24-15-3 Network.

Performance	E_{as}	K_{base}	K_{sub}
MSE	382,768.6559	665.3193099	2.655104275
NMSE	0.032939043	1.538228705	0.004111663
MAE(Mean Absolute Error)	342.0066288	8.329449027	0.824031822
Minimum Abs Error	1.855738014	0.011700513	0.000258325
Maximum Abs Error	8,077.777778	48.33333333	18.55078201
R	0.985435108	0.856186944	0.998683159

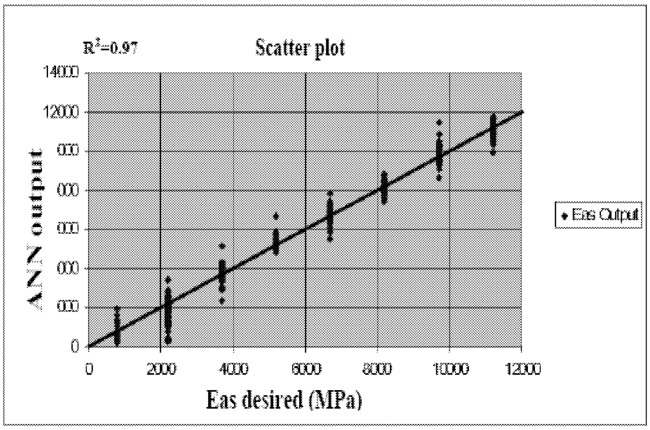

Fig. 6. ANN Prediction of Asphalt Modulus.

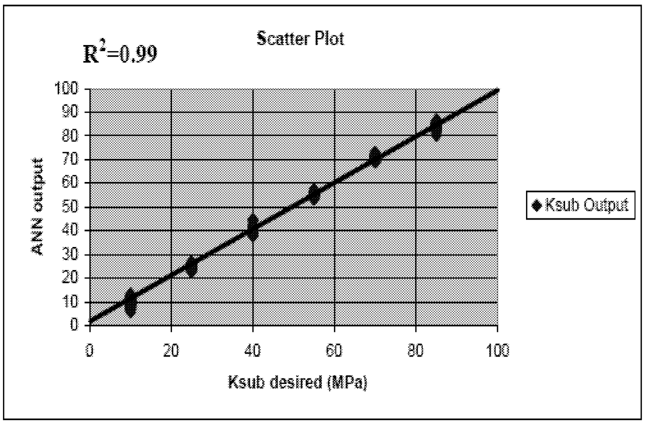

Fig. 7. ANN Prediction of Subgrade Modulus.

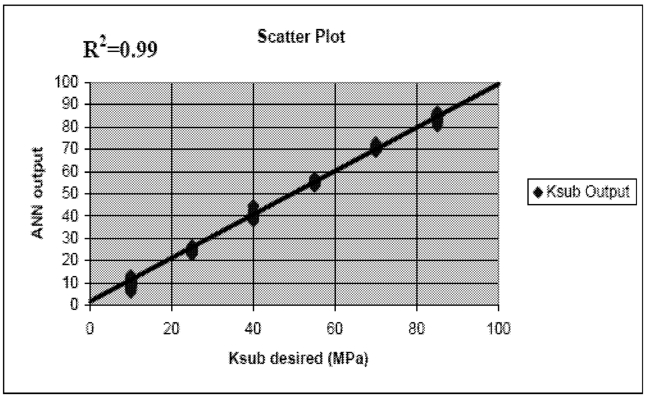

Fig. 8. ANN Prediction of Base Modulus.

case the network had 11 inputs which were 7 deflections, 2 thicknesses, in addition to E_{as}, and K_{sub} and a single output which was K_{base}. In order to determine the effect of each input parameter on K_{base}, a sensitivity analysis was carried out.

Sensitivity analysis provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to variation of an input. The first input is varied between its mean +/- a user-defined number of standard deviations while all other inputs are fixed at their respective means. The network output is computed for a user-defined number of steps above and below the mean.

Table 4. The Sensitivity Analysis on 11-25-6-1 Network.

Sensitivity (input)	K_{base} (output)
D0	144.7358875
D30	7.00376E-13
D60	376.888813
D90	517.9569747
D120	1.72131E-12
D150	725.2300913
D180	946.8826221
Has	4.209277386
Hbase	1.5533446
Eas	2.51504E-17
Ksub	3.33268E-15

Table 5. The Performance of the 11-25-6-1 Network in Predicting K_{base}.

Performance	K_{base}
MSE	70.31117574
NMSE	0.162560544
MAE	5.748000136
Min Abs Error	0.005092645
Max Abs Error	60.28405087
R	0.918971432

The results are shown in Table 4 which summarizes the variation of each output with respect to the variation in each input. Table 4 reports the standard deviation of each output divided by the standard deviation of the input which was varied to create the output. Table 4 shows that E_{as} and K_{sub} have some minor effects on K_{base}. It means that by adding these two parameters to the previous 9 input parameters and designing a network which has 11 inputs and a single output which is K_{base}, the chance of predicting the K_{base} more accurately may increase. The performance of the 11-25-6-1 network to predict the test data patterns is shown in Table 5.

Table 5 shows that the linear correlation coefficient is increased to 0.91 with 11-25-6-1 network.

Conclusions

ANN-based pavement backcalculation tools for analyzing the FWD data collected from Kenlayer program output have been developed in this study. Unlike the linear elastic assumptions commonly used in pavement layer backcalculation, realistic nonlinear unbound aggregate base and subgrade soils modulus models were used in the Kenlayer program. Kenlayer has not been used before in foreward-calculating and producing database for backcalculating. It concludes that Kenlayer can estimate the field deflection basin better than other softwares. The Genetic algorithms have been used to identify the best topology for the neural networks which are trained and tested to estimate the pavement layer moduli. Although the networks have less neurons than previous networks which have been used before for backcalculating, the coefficient of determination (R^2) in estimating the K_{base} and E_{as} is increased to 0.85 and 0.97. It is the first time that K_{base} and E_{as} are used as inputs for estimating K_{base}. The sensitivity analysis shows that using these two parameters as inputs can increase the performance of the network.

This study showed that multilayer perceptron artificial neural networks can be used to predict the moduli of the pavement layers fast and with good accuracy even if the forward calculation is based upon nonlinear assumptions.

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