Rapid Pavement Backcalculation Technique for Evaluating Flexible Pavement Systems

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ABSTRACT

This study focuses on the use of artificial neural network (ANN)-based pavement backcalculation tools for analyzing falling weight deflectometer (FWD) data collected from flexible pavement sections. Some of the pavement sites have been part of the Long-Term Pavement Performance (LTPP) program, and a history of pavement materials testing and FWD deflection data already exist in the LTPP database. Pavement backcalculation tools developed in this study have been utilized to predict the pavement layer moduli and critical pavement responses of flexible pavement layers under typical highway pavement loading conditions. Unlike the linear elastic layered theory commonly used in pavement layer backcalculation, nonlinear subgrade soil response models were used in the ILLI-PAVE finite element program to account for the softening nature of fine-grained subgrade soils and hardening behavior of the unbound base materials under increasing stress states. Preliminary investigations have shown that the ANN-based backcalculation models were capable of rapidly predicting the layer moduli and critical pavement responses with low average errors when compared to the models obtained directly from the finite element analyses. In addition to the analyses of large amounts of FWD data using the backcalculation tools developed in this study, predicted pavement layer moduli values were compared with the traditional backcalculation software solutions; the comparison results are presented in this paper. The advantages of using an ANN-based rapid pavement layer backcalculation tool are also discussed.

Key words: artificial neural networks—falling weight deflectometer—flexible pavements—long-term pavement performance—pavement layer backcalculation
INTRODUCTION

The falling weight deflectometer (FWD) is a commonly used device for non-destructively assessing the structural properties of flexible pavement systems. Evaluation of FWD test results entails the backcalculation of in situ pavement layer moduli from measured deflections. The use of artificial neural networks (ANNs) to backcalculate the elastic layer moduli and critical pavement responses are investigated using data from FWD test sites, including Iowa LTPP sections.

Elastic layered programs (ELPs) used in asphalt pavement analysis assume linear elasticity. Pavement geomaterials do not, however, follow a linear-type stress-strain behavior under repeated traffic loading. Rather, the nonlinear stress-sensitive response of unbound aggregate materials and fine-grained subgrade soils (herein referred to as geomaterials) has been well established (Brown and Pappin 1981; Thompson and Elliott 1985; Garg et al. 1998). Unbound aggregates exhibit stress hardening or stiffening, whereas fine-grained soils show stress softening type behavior. When these geomaterials are used as pavement layers, the layer stiffnesses (i.e., moduli) are no longer constant, but are functions of the applied stress state. Pavement structural analysis programs that take into account nonlinear geomaterial characterization, such as the ILLI-PAVE finite element program (Raad and Figueroa, 1980), need to be employed to predict pavement response needed more realistically for mechanistic-based pavement design.

Recent research at Iowa State University has focused on the development of artificial neural network (ANN)-based backcalculation flexible pavement analysis models to predict critical pavement responses and layer moduli, respectively. In the field, pavement deflection profiles are obtained from FWD measurements, which require the use of backcalculation structural analysis to determine pavement layer stiffnesses, and as a result estimate pavement remaining life. For this purpose, the ILLI-PAVE finite element program was utilized to generate a solution database for developing ANN-based structural models to predict pavement deflection basins accurately, and determine pavement layer moduli from realistic pavement surface deflection profiles or synthetic FWD data. Such a use of ANN models is described in this paper.

NON-DESTRUCTIVE TESTING WITH THE FALLING WEIGHT DEFLECTOMETER

The FWD, shown in Figure 1, is a non-destructive pavement loading device capable of exerting a load impulse similar in magnitude and duration to moving truck and aircraft wheel loads. The FWD unit can produce loads from 1,500 to 25,000 pounds of force. The load is applied to a loading plate by dropping a weight package on a dampening system, as illustrated in Figure 2. The force applied to the loading plate is measured by a load cell. The resulting pavement deflection is measured by a series of seven seismic deflection sensors positioned along the pavement surface at pre-determined intervals from the loading plate. Signals from the load cell and deflection sensors are fed into the system processor, which selects peak values and transfers this information to an onboard computer. A computerized system in the tow vehicle monitors and controls the testing cycle. A typical test sequence is approximately one minute long, so testing proceeds very rapidly down a street, highway, or airfield. The deflection data, as well as pavement stationing and operator comments, are stored on a floppy disk for analysis after uploading to a personal computer.

Deflection testing has numerous applications for the analysis and design of highway and airfield pavements. FWD data can be used to estimate subgrade and pavement layer elastic moduli values, determine the structural adequacy of a pavement and identify causes of failure, determine uniformity of support along a project and identify weak areas, determine overlay thickness requirements, and develop cost-effective maintenance and rehabilitation alternatives.
BACKGROUND ON THE LTPP DATABASE

The Long-Term Pavement Performance (LTPP) program is primarily designed to provide state of the art information to the state highway agencies to build and maintain longer lasting pavements (FHWA 1995). The LTPP database is a nationwide effort to collect pavement information over a long period of time. It contains a wide variety of information about pavement materials, climate, traffic, maintenance, field tests, etc. frequently collected for a particular pavement section. Thus, it provides a unique opportunity for pavement researchers to develop modeling tools.

Figure 3. General pavement studies (GPS) sites in Iowa
The LTPP program started in 1987 with a comprehensive 20-year study of in-service pavements and a series of rigorous long-term field experiments monitoring more than 2,400 flexible and rigid pavement test sections across the United States and Canada. LTPP database is mainly divided into the major categories of general pavement studies (GPS) and specific pavement studies (SPS). The GPS category consists of nearly 800 in-service pavement test sections throughout the United States and Canada. The SPS category includes intensive studies of specific variables involving new construction, maintenance treatments, and rehabilitation activities (LTPP 2004). Even though it contains a vast amount of information related to pavements, it is organized in a user-friendly format. The GPS and SPS sites in Iowa are shown in Figures 3 and 4, respectively.

OVERVIEW OF ARTIFICIAL NEURAL NETWORKS

Imitating the biological nervous system, artificial neural networks are information processing computational tools capable of solving nonlinear relations in a specific problem. Like humans, they have the flexibility to learn from examples by means of interconnected elements, namely neurons. Neural network architectures, arranged in layers, involve synaptic connections amid neurons that receive signals and transmit them to the others via activation functions. Each connection has its own weight and learning is the process of adjusting the weight between neurons to minimize error between the predicted and expected values. During the learning process, node biases are also adjusted, similar to the connection weights. Since interconnected neurons have the flexibility to adjust the weights, neural networks have powerful capacities for analyzing complex problems. Artificial neural networks, motivated by the neuronal architecture and operation of the brain, contribute to our understanding of several complex, nonlinear pavement engineering problems with various pavement and soil variables. In Figure 5, a typical structure of ANNs that consists of a number of neurons that are usually arranged in layers, which are the input layer, hidden layers, and output layers. A comprehensive description of ANNs is beyond the scope of this paper.
NONLINEAR GEOMATERIAL CHARACTERIZATION

Under the repeated application of moving traffic loads, most of the pavement deformations are recoverable and thus considered elastic. It has been customary to use resilient modulus (M_R) for the elastic stiffness of the pavement materials, defined as the repeatedly applied wheel load stress divided by the recoverable strain. Repeated load triaxial tests are commonly employed to evaluate the resilient properties of unbound aggregate materials and cohesive subgrade soils. Therefore, emphasis should be given in structural pavement analysis to realistic nonlinear material modeling in the base/subbase and subgrade layers primarily based on repeated load triaxial test results (AASHTO T307-99, European CEN Std EN 13286-7).

Simple resilient modulus models are often suitable for finite element programming and practical design use, such as in the following equations:

K-θ Model (Hicks and Monismith 1971):  
\[ M_R = K \left( \theta/p_0 \right)^\theta \]  
(1)

Universal Model (Uzan et al. 1992):  
\[ M_R = K_1 \left( \theta/p_0 \right)^{K_2} \left( \tau_{oct}/p_0 \right)^{K_3} \]  
(2)

Where \( \theta = \sigma_1 + \sigma_2 + \sigma_3 = \sigma_1 + 2\sigma_3 = \) bulk stress, \( \tau_{oct} = \) octahedral shear stress = \( \sqrt{2/3} \)σ_d (where \( \sigma_d = \sigma_1 - \sigma_3 = \) deviator stress in triaxial conditions), \( p_0 \) is the unit reference pressure (1 kPa or 1 psi) used in the models to make the stresses non-dimensional, and \( K, n, \) and \( K_1 \) to \( K_3 \) are multiple regression constants obtained from repeated load triaxial test data on granular materials. The simpler K-θ model often adequately captures the overall stress dependency (bulk stress effects) of unbound aggregate behavior under compression-type field loading conditions. The universal model (Uzan et al. 1992) additionally considers the effects of shear stresses and handles very well the modulus increase (unbound aggregates) or decrease (fine-grained soils) with increasing stress states, even for extension field loading conditions.

The resilient modulus of fine-grained subgrade soils is also dependent upon the stress state. Typically, soil modulus decreases in proportion to the increasing stress levels, thus exhibiting stress softening behavior. As a result, the most important parameter affecting the resilient modulus becomes the vertical...
deviator stress on top of the subgrade due to the applied wheel load. The bilinear or arithmetic model (Thompson and Elliot 1985) is a commonly used resilient modulus model for subgrade soils, expressed by the modulus-deviator stress relationship given in Figure 6. As indicated by Thompson and Elliot (1985), the value of the resilient modulus at the breakpoint in the bilinear curve, $E_{Ri}$, (see Figure 6) can be used to classify fine-grained soils as being soft, medium, or stiff.

where

$\sigma_d$: Deviator stress = $(\sigma_1 - \sigma_3)$

$E_{Ri}$: Breakpoint resilient modulus

$\sigma_{di}$: Breakpoint deviator stress

$K_3$, $K_4$ = Slopes

$\sigma_{dll}$: Deviator stress lower limit

$\sigma_{dul}$: Deviator stress upper limit

![Figure 6. Stress dependency of fine-grained soils characterized by the bilinear model](image)

### PAVEMENT ANALYSIS USING THE ILLI-PAVE FINITE ELEMENT PROGRAM

Developed at the University of Illinois (Raad and Figueroa 1980), ILLI-PAVE is an axisymmetric finite element program commonly used in the structural analysis of flexible pavements. The nonlinear, stress-dependent resilient modulus geomaterial models summarized in the previous section are already incorporated into ILLI-PAVE. Numerous studies have validated that the ILLI-PAVE model provides a realistic pavement structural response prediction for highway and airfield pavements (Thompson and Elliot 1985; Thompson 1992; Garg et al. 1998). Recent research at the Federal Aviation Administration’s Center of Excellence established at the University of Illinois also supported the development of an updated version of the program, now known as ILLI-PAVE 2000 (Gomez-Ramirez et al. 2002).

The ILLI-PAVE 2000 finite element program was used in this study as the main validated nonlinear structural model for analyzing flexible pavements. The goal was to establish a database of ILLI-PAVE response solutions that would eventually constitute the training and testing data sets for developing ANN-based structural models for rapid backcalculation analyses. For this purpose, a convergence study was performed to determine the domain size extent for the finite element mesh discretization. A radial boundary placed at 25 times the contact area radius was sufficient to obtain convergence of deflections.

The top surface asphalt course was characterized as a linear elastic material with Young’s Modulus, $E_{AC}$, and Poisson’s ratio, $\nu$. Due to its simplicity and ease in model parameter evaluation, the K-\(\theta\) model (Hicks and Monismith 1971) was used as the nonlinear characterization model for the unbound aggregate layer. Based on the work of Rada and Witczak (1981) with a comprehensive granular material database, $K$ and $n$ model parameters can be correlated to characterize the nonlinear stress-dependent behavior with only one model parameter using the following equation (Rada and Witczak, 1981):

$$\log_{10}(K) = 4.657 - 1.807 \cdot n \quad \text{R}^2 = 0.68; \text{SEE} = 0.22 \quad (3)$$

Accordingly, good quality granular materials, such as crushed stone, show higher $K$ and lower $n$ values, whereas the opposite applies for lower quality aggregates. Following the study by Rada and Witczak
(1981), the K-values used typically ranged from 20.7 MPa (3 ksi) to 62.0 MPa (9 ksi) and the corresponding n-values were obtained from Equation 3.

Fine-grained soils were considered to be no-friction rather than cohesion-only materials and were modeled using the bilinear or arithmetic model (see Figure 6) for modulus characterization. The breakpoint deviator stress, $E_{Ri}$, was the main input for subgrade soils. The $K_3$ and $K_4$ slopes shown in Figure 6 were taken as constants, 1,100 and 200, respectively, corresponding to medium soils given by Thompson and Elliott (1985). According to a comprehensive Illinois subgrade soil study by Thompson and Robnett (1979), the breakpoint deviator stress, $\sigma_{di}$, was taken as 41.4 kPa (6 psi), and 13.8 kPa (2 psi) was used for the lower limit deviator stress, $\sigma_{dll}$. The soil’s unconfined compressive strength, $Q_u$, or cohesion was used to determine the upper limit deviator stress, $\sigma_{dul}$ (see Figure 6), as a function of the breakpoint deviator stress, $E_{Ri}$, using the following relationship (Thompson and Robnett 1979):

$$\sigma_{dul} (psi) = 2 \times cohesion (psi) = Q_u (psi) = \frac{E_R (ksi) - 0.86}{0.307}$$  \hspace{1cm} (4)

Therefore, the asphalt concrete modulus, $E_{AC}$, granular base K-$\theta$ model parameter K, and the subgrade soil break point deviator stress, $E_{Ri}$, in the bilinear model were used as the layer stiffness inputs for all the different conventional flexible pavement ILLI-PAVE runs. The 40-kN (9-kip) wheel load was applied as a uniform pressure of 552 kPa (80 psi) over a circular area of radius 152 mm (6 in.). The thickness and moduli ranges used are also summarized in Table 1.

Table 1. Pavement geometry and material property/model inputs for ILLI-PAVE solutions

<table>
<thead>
<tr>
<th>Material type</th>
<th>Layer thickness</th>
<th>Material model</th>
<th>Layer modulus inputs</th>
<th>Poisson’s ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asphalt concrete</td>
<td>h$_{AC}$ = 76 to 381 mm</td>
<td>Linear elastic</td>
<td>$E_{AC}$ = 690 to 13,800 MPa (100 to 2,000 ksi)</td>
<td>$\nu = 0.35$</td>
</tr>
<tr>
<td>Unbound aggregate base</td>
<td>h$_{GB}$ = 102 to 559 mm</td>
<td>Nonlinear</td>
<td>$M_R = K\theta^n$</td>
<td>$\nu = 0.35$ for $K \geq 34.5$ MPa (5 ksi) $\nu = 0.40$ for $K &lt; 34.5$ MPa (5 ksi)</td>
</tr>
<tr>
<td>Fine-grained subgrade</td>
<td>7,620 mm (300 in.)</td>
<td>Nonlinear bilinear model</td>
<td>$E_{Ri} = 6.9$ to 96.5 MPa (1 to 14 ksi)</td>
<td>$\nu = 0.45$</td>
</tr>
</tbody>
</table>

ARTIFICIAL NEURAL NETWORKS AS PAVEMENT ANALYSIS TOOLS

Backpropagation artificial neural network models were trained in this study with the results from the ILLI-PAVE 2000 finite element model and were used as rapid analysis design tools for predicting stresses and strains in flexible pavements. Backpropagation ANNs are very powerful and versatile networks that can be taught to map from one data space to another using a representative set of patterns/examples to be learned. “Backpropagation network” actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. The learning process performed by this algorithm is called backpropagation learning, which is mainly an error minimization technique (see Haykin 1999).

ANNs are valuable computational tools that are increasingly being used to solve resource-intensive complex problems as an alternative to using more traditional techniques. Meier et al. (1997) trained backpropagation ANNs as surrogates for ELP analysis in a computer program for backcalculating pavement layer moduli and realized a 42-fold increase in processing speed. In a recent successful
Bayrak, Guclu, Ceylan (2002) employed ANNs in the analysis of concrete pavement systems and developed ANN-based design tools that incorporated state-of-the-art finite element solutions into routine practical design in ways that were several orders of magnitude faster than the sophisticated finite element programs. Most recently, the project team working on the development of the new mechanistic-based AASHTO pavement design (NCHRP1-37A) in the United States has also recognized ANNs as nontraditional but very powerful computing techniques, and took advantage of ANN models in preparing a mechanistic concrete pavement analysis package.

A total of 24,093 ILLI-PAVE FE runs were conducted by randomly choosing the pavement layer thicknesses and input variables within the given ranges in Table 1 to generate a knowledge database for ANN trainings. The total analysis depth of the pavement system was taken as 7,620 mm (300 in.). The subgrade thicknesses were calculated by subtracting the thicknesses of the asphalt concrete (AC) layer and the base from the total analysis depth. The outputs recorded were the pavement surface deflection basin and the critical pavement responses, the radial strain at the bottom of the AC layer (ε_{AC}), the vertical strain on top of the subgrade (ε_{SG}), and the deviator stress on top of the subgrade layer (σ_{D}). To maintain a high level of accuracy in the results from all finite element analyses, very similar ILLI-PAVE meshes were employed to have 266 to 494 elements with a total of 20 nodes used in the horizontal direction and 15 to 27 nodes used in the vertical direction. Ceylan (2002) recently highlighted the need to choose such consistent meshes for generating accurate finite element solutions and, as a result, successfully training ANN structural analysis models.

Backpropagation neural networks were used to develop three ANN structural models with different network architectures for predicting the pavement layer moduli (E_{AC}, K_{GB}, and E_{RI}) and critical pavement responses (ε_{AC}, ε_{SG}, and σ_{D}) using the FWD deflection data (see Table 2). The FWD surface deflections (D_{0}, D_{8}, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60}, and D_{72}) are often collected at several different locations, at the drop location (0) and at radial offsets of 203 mm (8 in.), 254 mm (12 in.), 457 mm (18 in.), 610 mm (24 in.), 914 mm (36 in.), 1219 mm (48 in.), 1524 mm (60 in.), and 1829 mm (72 in.). For the modeling work, surface deflections at these FWD sensor radial offsets were obtained from the ILLI-PAVE solutions and used as synthetic data to train ANNs.

Table 2. Conventional flexible pavement ANN backcalculation models

<table>
<thead>
<tr>
<th>ANN models</th>
<th>Input parameters</th>
<th>Output variables</th>
<th>ANN architecture</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCM-1</td>
<td>h_{AC}, h_{GB}, D_{0}, D_{12}, D_{24}, D_{36}</td>
<td>E_{AC}, E_{RI}</td>
<td>6 – 20 – 20 – 2</td>
</tr>
<tr>
<td>BCM-2</td>
<td>h_{AC}, h_{GB}, D_{0}, D_{8}, D_{12}, D_{24}, D_{36}, E_{AC}, E_{RI}</td>
<td>K_{GB}</td>
<td>12 – 20 – 20 – 1</td>
</tr>
<tr>
<td>BCM-3</td>
<td>h_{AC}, h_{GB}, D_{0}, D_{12}, D_{24}, D_{36}</td>
<td>ε_{AC}, ε_{SG}, σ_{D}</td>
<td>6 – 20 – 20 – 3</td>
</tr>
</tbody>
</table>

The first backcalculation model, BCM-1, was designed to predict E_{AC} of the AC layer and the E_{RI} value of the subgrade using only four pavement surface deflections, D_{0}, D_{12}, D_{24}, and D_{36}, and two layer thicknesses, h_{AC}, h_{GB}. The ANN BCM-1 model, therefore, had six input parameters and two outputs, E_{AC} and E_{RI}. A training data file was formed using the 24,093 ILLI-PAVE runs. One thousand of these runs were set aside for use as an independent testing set to conduct proper training and validate the performance of the trained ANN BCM-1 model. A neural network architecture with two hidden layers was exclusively chosen in accordance with the satisfactory results obtained previously with such networks, considering their ability to better facilitate the nonlinear functional mapping (Ceylan 2002).

Several network architectures with two hidden layers were trained. Overall, the training and testing mean squared errors (MSEs) decreased as the networks grew in size with increasing numbers of neurons in the hidden layers. The testing MSEs for the two output variables were, in general, slightly lower than the training ones. The error levels for both the training and testing sets matched closely when the number of
hidden nodes approached 20, as in the case of 6-20-20-2 network architecture (6 input, 20 and 20 hidden, and 2 output nodes, respectively).

Figure 7 depicts the prediction ability of the 6-20-20-2 network at the 10,000th training epoch. Average absolute errors (AAEs) were calculated as the sum of the individual absolute errors divided by the 1,000 independent testing patterns. The AAE for the AC layer moduli was a low 1.22%, while the AAE for the subgrade breakpoint moduli $E_{Bi}$ was only 3.27%. As shown in Figure 7, all 1,000 ANN predictions fell on the line of equality for the two-pavement layer moduli, thus indicating proper training and excellent performance of the ANN BCM-1 model.

The development of a second backcalculation model, ANN BCM-2, was deemed necessary for accurately predicting the $K$ parameter of the $K^0$ granular base model. The $E_{AC}$ and $E_{RI}$, already computed from the ANN BCM-1 model, were used as additional input variables in the BCM-2 model. The BCM-2 network architecture had 12 input variables ($h_{AC}$, $h_{GB}$, $D_0$, $D_{8}$, $D_{12}$, $D_{24}$, $D_{36}$, $D_{48}$, $D_{60}$, $D_{72}$, $E_{AC}$, and $E_{RI}$) and a single output, for the $K$ parameter. The trained ANN BCM-2 also had 2 hidden layers with 20 hidden nodes in each layer, and successfully predicted the $K$ values with a low AAE value of 3.53% after 10,000 learning cycles.

Next, using ILLI-PAVE solutions, a third backcalculation model, ANN BCM-3, was developed with the intention of directly predicting the critical pavement responses, $\varepsilon_{AC}$, $\varepsilon_{SG}$, and $\sigma_D$, from the deflection basins. This approach eliminates the need for first predicting the pavement layer moduli and then using a forward calculation structural analysis model to compute the critical pavement responses. The directness of this approach can save time and effort in analyzing the structural adequacy of field pavement sections from FWD data. Once validated with field data, the ANN model can predict $\varepsilon_{AC}$ for AC fatigue condition evaluation in the field.

The ANN BCM-3 network architecture had 6 input variables (inputs similar to those of the ANN BCM-1 model), 2 hidden layers with 20 hidden nodes in each layer, and 3 critical pavement responses, $\varepsilon_{AC}$, $\varepsilon_{SG}$, and $\sigma_D$, in the output layer. The AAE values from the ANN BCM-3 predictions were 0.46% and 2.03% for the asphalt radial strains ($\varepsilon_{AC}$) and the vertical compressive subgrade strains ($\varepsilon_{SG}$), respectively. The AAE value for the predicted subgrade deviator stresses ($\sigma_D$) was 1.36%. Such low errors indicate the
proper training and excellent prediction performance of the ANN BCM-3 backcalculation model trained for 10,000 learning cycles.

To develop more robust networks that can tolerate the noisy or inaccurate pavement deflection patterns collected from FWD field tests, several network architectures were trained with varying levels of noise in them. Applied noise levels in deflection basins and pavement layer thicknesses ranged from ± 2% to ± 10% to train the robust ANN models that can account for the variations in deflection measurements and pavement layer thicknesses due to poor construction practices. The AAE comparisons for the virgin data and noise-introduced data are given below.

AAE variations for the asphalt layer moduli predictions were investigated. The minimum AAE was obtained in the ANN training that used virgin deflection data. As can be seen from Figure 8, when the noise level introduced into the deflection data was increased, the percent AAE value also increased, as expected. After noise was introduced to the deflection data, the highest AAE value increase was found in the KGB predictions. AAE variations for predicting the critical pavement responses were also investigated. Similar trends in AAE increase in the asphalt layer moduli predictions were observed in predicting the critical pavement responses. The percent AAE value was increased again when more noise was introduced into the deflection data (see Figure 9).

![Figure 8. AAE variations for predicting the asphalt layer moduli for different noise levels](image)

<table>
<thead>
<tr>
<th></th>
<th>Virgin Def.</th>
<th>±2% Noisy Def.</th>
<th>±5% Noisy Def.</th>
<th>±10% Noisy Def.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAC</td>
<td>1.22</td>
<td>2.77</td>
<td>4.85</td>
<td>7.41</td>
</tr>
<tr>
<td>ERI</td>
<td>3.27</td>
<td>5.19</td>
<td>6.57</td>
<td>8.03</td>
</tr>
<tr>
<td>KGB</td>
<td>3.53</td>
<td>10.04</td>
<td>15.62</td>
<td>22.12</td>
</tr>
</tbody>
</table>
PERFORMANCE OF ANN PAVEMENT BACKCALCULATION MODELS

Six conventional flexible pavement sections were selected to further evaluate the performances of the ANN backcalculation models, BCM-1, BCM-2, and BCM-3. All pavement sections had a 102-mm (4-in.) AC underlain by a 305-mm (12-in.) granular base layer and applied with the 40-kN (9-kip) wheel load and a 552-kPa (80-psi) uniform tire pressure. The AC layer moduli were kept constant at 1,379 MPa (200 ksi) with a constant Poisson’s ratio of 0.35.

The pavements were first analyzed with the ILLI-PAVE finite element program. Two aggregate base K values of 27.6 and 62.1 MPa (4 and 9 ksi) and three subgrade ERi values of 20.7, 41.4, and 62.1 MPa (3, 6, and 9 ksi) were considered for a total factorial of 6 pavement sections analyzed. The rest of the nonlinear model parameters in the base and subgrade layers were assigned in accordance with the properties shown in Table 3. The pavement surface deflections obtained by ILLI-PAVE at 0, 203, 305, 610, 914, 1,219, 1,524, and 1,829 mm (0, 8, 12, 24, 36, 48, 60, and 72 in.) were treated as field-measured FWD deflections and used for validating the ANN backcalculation model performances. These deflections were also used in an ELP-based backcalculation program, BAKFAA, developed by the Federal Aviation Administration, to backcalculate the pavement layer moduli (http://www.airtech.tc.faa.gov/naptf/download/).

The top section of Table 3 presents the inputs and output results of the ILLI-PAVE analyses. Given next in Table 3 are the ANN backcalculation model predictions for the AC layer modulus, EAC, nonlinear parameters, K and ERi, and the critical pavement responses, εAC, εSG, and σD. Note that all ANN models produced very close results to the ILLI-PAVE input values and critical pavement responses. The AAE values were 2.1% for the six EAC predictions and 1.7% for the six ERi predictions from the ANN BCM-1 model, 3.4% for the six K predictions from the ANN BCM-2 model, and 0.5%, 1.5%, and 1.3% for each of the six predicted critical pavement responses for εAC, εSG, and σD, respectively, from the ANN BCM-3.
model. Clearly, the developed ANN models were quite successful in accurately mapping the nonlinear analysis ability of the ILLI-PAVE finite element program into their connection weights and node biases. The AAE values for the predicted critical pavement responses were even lower than the ones obtained for the backcalculated layer properties, which suggests that it would be feasible to estimate, for example, pavement fatigue life directly from the field-measured FWD deflection data.

Table 3. Summary analysis results for the six pavements with unbound aggregate bases

<table>
<thead>
<tr>
<th>Pavement section</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAC (MPa) – input</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
</tr>
<tr>
<td>K (MPa) – input</td>
<td>27.6</td>
<td>27.6</td>
<td>27.6</td>
<td>62.1</td>
<td>62.1</td>
<td>62.1</td>
</tr>
<tr>
<td>ERI (MPa) – input</td>
<td>20.7</td>
<td>41.4</td>
<td>62.1</td>
<td>20.7</td>
<td>41.4</td>
<td>62.1</td>
</tr>
<tr>
<td>εAC (με) – output (tension “+)</td>
<td>426</td>
<td>411</td>
<td>400</td>
<td>355</td>
<td>346</td>
<td>340</td>
</tr>
<tr>
<td>εSG (με) – output (compression “−)</td>
<td>-1,058</td>
<td>-925</td>
<td>-792</td>
<td>-929</td>
<td>-798</td>
<td>-698</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ANN backcalculation model predictions</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAC (MPa) – (ANN BCM-1)</td>
<td>1,333</td>
<td>1,328</td>
<td>1,373</td>
<td>1,387</td>
<td>1,428</td>
<td>1,389</td>
</tr>
<tr>
<td>K (MPa) – (ANN BCM-2)</td>
<td>28.1</td>
<td>28.6</td>
<td>27.3</td>
<td>64.5</td>
<td>65.2</td>
<td>64.9</td>
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<tr>
<td>ERI (MPa) – (ANN BCM-1)</td>
<td>20.7</td>
<td>40.6</td>
<td>61.7</td>
<td>21.1</td>
<td>42.8</td>
<td>63.7</td>
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<tr>
<td>εAC (με) – (ANN BCM-3)</td>
<td>425</td>
<td>408</td>
<td>400</td>
<td>352</td>
<td>344</td>
<td>339</td>
</tr>
<tr>
<td>εSG (με) – (ANN BCM-3)</td>
<td>-1,009</td>
<td>-923</td>
<td>-763</td>
<td>-925</td>
<td>-797</td>
<td>-697</td>
</tr>
<tr>
<td>σD (kPa) – (ANN BCM-3)</td>
<td>-38</td>
<td>-40</td>
<td>-48</td>
<td>-34</td>
<td>-39</td>
<td>-43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BAKFAA ELP-based results</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAC (MPa) – backcalc. output</td>
<td>1,498</td>
<td>1,579</td>
<td>1,497</td>
<td>1,553</td>
<td>1,551</td>
<td>1,555</td>
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<tr>
<td>EGB (MPa) – backcalc. output</td>
<td>129.3</td>
<td>127.9</td>
<td>148.0</td>
<td>158.2</td>
<td>167.5</td>
<td>174.6</td>
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<tr>
<td>ESG (MPa) – backcalc. output</td>
<td>60.4</td>
<td>86.7</td>
<td>103.7</td>
<td>66.9</td>
<td>91.5</td>
<td>115.7</td>
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<tr>
<td>εAC (με) – forward calc. output</td>
<td>520</td>
<td>505</td>
<td>473</td>
<td>444</td>
<td>425</td>
<td>411</td>
</tr>
<tr>
<td>εSG (με) – forward calc. output</td>
<td>-861</td>
<td>-688</td>
<td>-608</td>
<td>-748</td>
<td>-614</td>
<td>-525</td>
</tr>
<tr>
<td>σD (kPa) – forward calc. output</td>
<td>-52</td>
<td>-59</td>
<td>-63</td>
<td>-50</td>
<td>-56</td>
<td>-60</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>BAKFAA forward calculations with avg. nonlinear layer moduli</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAC (MPa) – avg. from ILLI-PAVE</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
<td>1,379</td>
</tr>
<tr>
<td>EGB (MPa) – avg. from ILLI-PAVE</td>
<td>193.4</td>
<td>201.0</td>
<td>207.5</td>
<td>223.4</td>
<td>229.2</td>
<td>233.7</td>
</tr>
<tr>
<td>ESG (MPa) – avg. from ILLI-PAVE</td>
<td>40.4</td>
<td>57.7</td>
<td>76.6</td>
<td>42.1</td>
<td>59.3</td>
<td>77.2</td>
</tr>
<tr>
<td>εAC (με) – forward calc. output</td>
<td>420</td>
<td>407</td>
<td>396</td>
<td>366</td>
<td>357</td>
<td>351</td>
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<tr>
<td>εSG (με) – forward calc. output</td>
<td>-935</td>
<td>-788</td>
<td>-688</td>
<td>-857</td>
<td>-728</td>
<td>-635</td>
</tr>
<tr>
<td>σD (kPa) – forward calc. output</td>
<td>-38</td>
<td>-45</td>
<td>-52</td>
<td>-36</td>
<td>-43</td>
<td>-49</td>
</tr>
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</table>

The ELP-based BAKFAA program was used next to backcalculate the average elastic layer moduli from pavement surface deflections. Table 3 also summarizes the BAKFAA backcalculation and forward calculation results. The AAE values were rather high: 12%, 170%, and 78% for each of the six predicted moduli for EAC, EGB, and ESG, respectively. These layer moduli were then used as inputs for the forward calculation option of the BAKFAA program to compute critical pavement responses. The AAE values were 22%, 23%, and 39% for the average εAC, εSG, and σD values, respectively, when compared to the actual ILLI-PAVE pavement responses.
Also presented in the bottom section of Table 3 are the results of additional BAKFAA forward calculation analyses. For all six pavement sections, the subgrade and base layer moduli, $E_{SG}$ and $E_{GB}$, were computed by averaging the actual ILLI-PAVE computed nonlinear (pavement centerline) modulus distributions with depth in the subgrade and base layers. These averaged moduli values, tabulated in the bottom section of Table 3, were then used as inputs in the forward calculation BAKFAA analyses to predict the critical pavement responses. In this case, the AAE values were calculated as 2%, 11%, and 8% for the average $\varepsilon_{AC}$, $\varepsilon_{SG}$, and $\sigma_D$ values, respectively, much lower than the previous AAE values of 22%, 23%, and 39% from the ELP-based backcalculation. Again, the nonlinear pavement geomaterial behavior must be properly accounted for to backcalculate layer moduli and predict critical pavement responses accurately.

**SUMMARY AND CONCLUSIONS**

ANN-based pavement backcalculation tools for analyzing the FWD data collected from flexible pavement sections have been developed in this study. Some of the pavement sites have been part of the LTPP program, and a history of pavement materials testing and FWD deflection data already exist in the LTPP database. Three ANN backcalculation models were developed using approximately 24,000 nonlinear ILLI-PAVE finite element solutions. Unlike the linear elastic layered theory commonly used in pavement layer backcalculation, realistic nonlinear unbound aggregate base (UAB) and subgrade soil modulus models were used in the ILLI-PAVE program to account for the typical stiffening behavior of UABs and the fine-grained subgrade soil moduli decreasing with increasing stress states. The ANN models developed successfully predicted the layer moduli and critical pavement responses computed by the ILLI-PAVE finite element solutions and were superior to the linear elastic layered backcalculation analyses due to the nonlinear material characterization employed. Also, in order to develop more robust networks that can tolerate the noisy or inaccurate pavement deflection patterns collected from FWD field tests, several network architectures were trained with varying levels of noise; the noise-introduced ANN models successfully predicted the pavement layer moduli and critical pavement responses. Such ANN structural analysis models can provide pavement engineers and designers with sophisticated finite element solutions, without the need for a high degree of expertise in the input and output of the problem, to rapidly analyze the large number of pavement deflection basins needed for routine pavement evaluation.
REFERENCES


