Prediction of National Airport Pavement Test Facility Pavement Layer Moduli from Heavy Weight Deflectometer Test Data Using Artificial Neural Networks

Kasthurirangan Gopalakrishnan
Department of Civil, Construction and Environmental Engineering
Iowa State University
192 Town Engineering Building
Ames, IA 50011
rangan@iastate.edu

ABSTRACT

The National Airport Pavement Test Facility (NAPTF) was constructed to generate full-scale testing data to investigate the performance of airport pavements subjected to complex gear loading configurations of new generation aircraft. During the first test program, the NAPTF test sections were simultaneously subjected to Boeing 777 trafficking in one lane and Boeing 747 trafficking in another lane using the National Airport Pavement Test Machine. To monitor the effect of time and traffic on pavement structural responses, heavy weight deflectometer (HWD) tests were conducted on the trafficked lanes and the untrafficked centerline of flexible test sections as trafficking progressed.

The primary objective of this study was to develop a tool for backcalculating NAPTF non-linear flexible pavement layer moduli from HWD data using artificial neural networks (ANN). A multi-layer, feed-forward network that uses an error-backpropagation algorithm was trained to approximate the HWD backcalculation function. The synthetic database generated using the non-linear pavement finite element program, ILLI-PAVE, was used to train the ANN. Using the ANN, the asphalt concrete moduli and subgrade moduli were successfully predicted. Further research is required to develop ANN models for predicting the granular layer moduli. These results could be used to compare the relative effect of Boeing 777 and Boeing 747 trafficking on the elastic moduli and characterize the seasonal variation in moduli values. The same concept could also be used for backcalculating non-linear pavement moduli of highway pavements for input into mechanistic-empirical analysis and design.

Key words: artificial neural networks—ILLI-PAVE—National Airport Pavement Test Facility—pavement moduli

Proceedings of the 2005 Mid-Continent Transportation Research Symposium, Ames, Iowa, August 2005.

INTRODUCTION

The Federal Aviation Administration's (FAA) National Airport Pavement Test Facility (NAPTF) is located at the Atlantic City International Airport, New Jersey. It was constructed to generate full-scale test data needed to develop pavement design procedures for the new generation of large civil transport aircraft, including the Boeing 777 and Boeing 747. During the first series of tests, two gear configurations, a six-wheel tridem landing gear (Boeing 777) in one lane and a four-wheel dual-tandem landing gear (Boeing 747) in the other lane, were tested simultaneously. Heavy weight deflectometer (HWD) tests were conducted at regular time intervals as trafficking continued. The primary objective of this study was to develop a tool for backcalculating NAPTF non-linear pavement layer moduli from HWD test data using artificial neural networks (ANN).

The elastic layer moduli backcalculated from non-destructive test results are good indicators of pavement layer condition (Xu, Ranjinathan, and Kim 2001) as well as required inputs for the a priori mechanistic design of a flexible pavement. The backcalculation approach is particularly appealing for characterizing subgrade soils that display large variability in subgrade modulus (as large as 35%–50% over few miles of a pavement) (Thompson, Tutumluer, and Bejarano 1998).

Conventional elastic layer program (ELP)-based backcalculation software assumes that pavement materials are linear-elastic, homogenous, and isotropic. The non-linearity or stress-dependency of resilient modulus for unbound granular materials and cohesive fine-grained subgrade soils is well documented in the literature (Hicks 1970; Thompson and Robnett 1979). Previous studies have observed the non-linearity of underlying layers at the NAPTF. Gomez-Ramirez and Thompson (Garg and Marsey 2002) reported the presence of material non-linearity at NAPTF by separately analyzing the individual layer compression from multi-depth deflectometer (MDD) readings. Garg and Marsey (2002) have similarly observed the stress-dependent nature of the granular and subgrade layers in NAPTF flexible test sections. Therefore, it is more realistic to use non-linear layer moduli for conducting NAPTF pavement structural analysis and for studying the variation in moduli with trafficking.

ILLI-PAVE is a two-dimensional axi-symmetric pavement finite-element software developed at the University of Illinois at Urbana-Champaign (UIUC) (Raad and Figueroa 1980). It incorporates stress-sensitive material models and provides a more realistic representation of the pavement structure and its response to loading (NCHRP 1990). Based on extensive repeated laboratory testing data at UIUC, Thompson and Robnett (1979) indicated that the breakpoint resilient modulus (E_{Ri}), typically associated with a repeated deviator stress of about six psi, is a good indicator of the subgrade soil's resilient modulus. The Asphalt Institute's Thickness Design Manual MS-1 (Asphalt Institute 1982) recommends E_{Ri} (subgrade modulus at a deviator stress of six psi) as the subgrade modulus input for ELP analysis. The E_{Ri} is also one of the subgrade material property inputs to ILLI-PAVE. However, there is no commercial ILLI-PAVE-based backcalculation program currently available. Previous research at UIUC showed that the asphalt concrete moduli and non-linear subgrade moduli (E_{Ri}) could be successfully predicted using an ANN trained with the ILLI-PAVE database (Gopalakrishnan and Thompson 2004). Ceylan et al. (2004) demonstrated the use of ANNs trained with ILLI-PAVE results as pavement structural analysis tools for the rapid and accurate prediction of critical responses and deflection profiles of flexible pavements subjected to typical highway loadings. Ongoing research at Iowa State University on backcalculting pavement moduli using ANN is being performed under Dr. Halil Ceylan's supervision. However, the current research specifically focuses on developing a tool for backcalculating NAPTF pavement non-linear moduli using ANN trained with ILLI-PAVE results.

NATIONAL AIRPORT PAVEMENT TEST FACILITY

The NAPTF test pavement area is 900 feet (274.3 meters) long and 60 feet (18.3 meters) wide. The first test series installation included a total of nine test sections (six flexible and three rigid) built on three different subgrade materials: low-strength (target CBR of 4), medium-strength (target CBR of 8), and high-strength (target CBR of 20). Two different base sections are used in flexible test sections: conventional (granular) and stabilized (asphalt concrete). The low-strength and the medium-strength flexible test sections alone are considered in this study. The naturally occurring sandy soil material at the NAPTF site underlies each subgrade layer.

Pavement Sections

Each NAPTF test section is identified using a three-character code, where the first character indicates the subgrade strength (L for low, M for medium, and H for high), the second character indicates the test pavement type (F for flexible and R for rigid), and the third character signifies whether the base material is conventional-aggregate (C) or asphalt-stabilized (S). Thus, test section MFC refers to a conventional-base flexible pavement built over a medium strength subgrade, whereas test section MFS refers to a stabilized-base flexible pavement built over a medium-strength subgrade. Cross-sectional views of the as-built NAPTF flexible test items considered in this study are shown in Figure 1. Note that P-401 asphalt concrete was used in the surface layer and in the stabilized base layer as well.

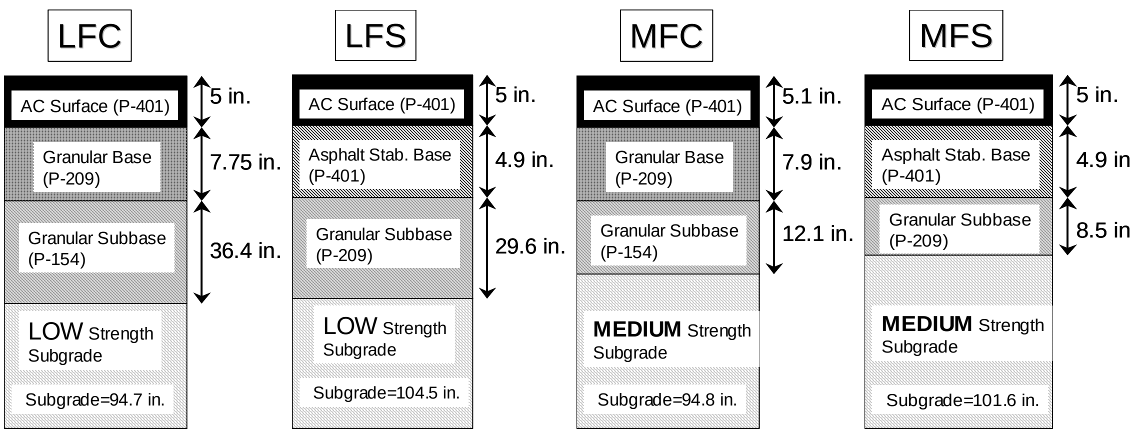

Figure 1. Cross-sectional views of as-built NAPTF flexible test sections

Traffic Testing

A six-wheel dual-tridem gear configuration (Boeing 777) with 54-inch (1,372-mm) dual spacing and 57-inch (1,448-mm) tandem spacing was loaded on the north wheel track, while the south side was loaded with a four-wheel dual-tandem gear configuration (Boeing 747) having 44-inch (1,118-mm) dual spacing and 58-inch (1,473-mm) tandem spacing. The wheel loads were set to 45,000 lbs (20.4 tons) each and the tire pressure (cold) was 188 psi (1,295 Kpa). In the LFC (a conventional aggregate-base pavement built over low-strength subgrade) and LFS (an asphalt-stabilized base pavement built over low-strength subgrade) test sections, the wheel loads were increased from 45,000 lbs (20.4 tons) to 65,000 lbs (29.4 tons) after 20,000 initial load repetitions. Throughout the traffic test program, the traffic speed was 5 mph (8 kmh).

NAPTF Flexible Pavement Failure Criterion

The NAPTF failure criterion is based on the criterion utilized by the U.S. COE MWHGL Tests (Ahlvin et al. 1971). It is defined as 1-inch (25.4-mm) surface upheaval adjacent to the traffic lane. This is considered to reflect a structural or shearing failure in the subgrade.

Data Availability

All test data referenced in this paper are available for download on the FAA Airport Pavement Technology website: http://www.airporttech.tc.faa.gov/naptf/.

HEAVY WEIGHT DEFLECTOMETER TESTS

For HWD testing, the FAA HWD KUAB Model 240, configured with a 12-inch loading plate and a 27–30 msec pulse width, was used. The deflections were measured with seven seismometers at offsets of 0-inch (D_0), 12-inch (305-mm) (D_{12}), 24-inch (610-mm) (D_{24}), 36-inch (914-mm) (D_{36}), 48-inches (1,219-mm) (D_{48}), and 60-inch (1,524-mm) (D_{60}) intervals from the center of the load.

The HWD tests were performed at nominal force amplitudes of 12,000 lbs or 12 kip (53.4 kN), 24,000 lbs or 24 kip (106.8 kN), and 36,000 lbs or 36 kip (160.2 kN). These tests were performed on the centerline, Boeing 777 traffic lane (Lane 2) and Boeing 747 traffic lane (Lane 5). The HWD test sequences were repeated at 10-foot (3.1-meter) intervals along the test lanes. The location and orientation of HWD test lanes are illustrated in Figure 2.

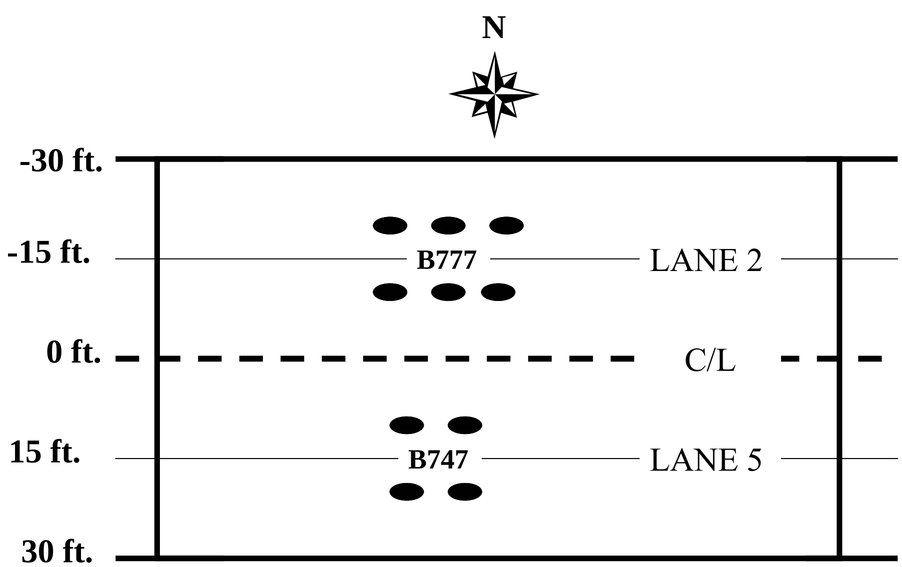

Figure 2. NAPTF HWD test lanes

Pavement Temperature

The temperature of the asphalt concrete layer at the time of FWD testing has a significant influence on the surface deflections. During the NAPTF construction, static temperature sensors were installed at different depths along the test sections to record the pavement temperatures at different times of the day. The HWD tests were all conducted between January 11, 2000 and June 6, 2001. The asphalt concrete temperature varied between 40 ^{0}F to 75 ^{0}F during the entire duration of traffic testing.

DATABASE GENERATION USING ILLI-PAVE

To generate the synthetic database for training the ANN, each NAPTF flexible test section was modeled in ILLI-PAVE. The as-constructed layer thicknesses (see Figure 1) were used for each test section. The individual pavement layers were characterized as follows. The asphalt concrete layer and the sand layer were treated as linear elastic material. Stress-dependent elastic models along with Mohr-Coulomb failure criteria were applied for the base, subbase, and subgrade layers. The stress-hardening K-θ model was used for the base and subbase layers:

$$M_R = \frac{\sigma_D}{\varepsilon_R} = K\theta^n \tag{1}$$

Where M_R is resilient modulus (psi), θ is bulk stress (psi), and K and n are statistical parameters.

The following relationship exists between K and n (R^2 = 0.68, SEE = 0.22) (Rada and Witczak 1981):

$$\text{Log}_{10}(K) = 4.657 - 1.807n \tag{2}$$

The stress-softening bilinear model was used for the subgrade layer:

$$\begin{aligned} M_R &= M_{Ri} + K_1.(\sigma_d - \sigma_{di}) \quad \text{for } \sigma_d < \sigma_{di} \\ M_R &= M_{Ri} + K_2.(\sigma_d - \sigma_{di}) \quad \text{for } \sigma_d > \sigma_{di} \end{aligned} \tag{3}$$

Where M_R is resilient modulus (psi), σ_d is applied deviator stress (psi), and K_1 and K_2 are statistically determined coefficients from laboratory tests.

A total of 5,000 input cases were generated for each test section by randomly varying the asphalt concrete and subgrade layer moduli and the 'K_b'-'n_b' and 'K_s'-'n_s' values (note that K and n are related) for the base and subbase layers, respectively. The effect of 36-kip HWD loading was simulated in ILLI-PAVE and the pavement surface deflections were computed. Initially, it was decided to use separate ANN models for each section. Of the total number of data sets for each test section, 3,750 data vectors were used in training the ANN and the remaining 1,250 data vectors were used to test the network after the training was completed. The range of layer properties used in training the ANN is summarized in Table 1.

ARTIFICIAL NEURAL NETWORK ARCHITECTURE

A generalized n-layer feedforward ANN that uses an error-backpropogation algorithm (Haykin 1994) was implemented in the Visual Basic (VB 6.0) programming language. The program can allow for a general number of inputs, hidden layers, hidden layer elements, and output layer elements. Two hidden layers were found to be sufficient for solving a problem of this size, and therefore the architecture was reduced to a four-layer feedforward network. A four-layer feedforward network consists of a set of sensory units (source nodes) that constitute the input layer, two hidden layers of computation nodes, and an output layer of computation nodes. The following notation is generally used to refer to a particular type of architecture that has two hidden layers: (# inputs)-(# hidden neurons)-(# hidden neurons)-(# outputs). For example, the notation 10-40-40-3 refers to an ANN architecture that takes in 10 inputs (features), has 2 hidden layers consisting of 40 neurons each, and produces 3 outputs.

Table 1. Range of pavement layer properties used in generating the ANN training database

Pavement layer	Thickness (inches)	Elastic layer modulus (ksi)	Poisson's ratio
Asphalt concrete	5 - MFC &LFC 10 - MFS & LFS	100 – 2,500	0.35
Base	8 - MFC & LFC 8.5 - MFS 29.5 - LFS	K_b: 1.6 – 20 n_b: 0.2 – 0.8	0.35
Subbase	12 - MFC 36.4 - LFC	K_s: 1.6 – 20 n_s: 0.2 – 0.8	0.35
Subgrade	95 - MFC & LFC 105 - MFS & LFS	1.6 – 20	0.45
Sand	120 - Medium 144 - Low	45	0.4

An ANN-based backcalculation procedure was developed to approximate the HWD backcalculation function. Using the ILLI-PAVE synthetic database, the ANN was trained to learn the relationship between the synthetic deflection basins (inputs) and the pavement layer moduli (outputs).

Initialization of Weights

The first step in back-propogation learning is to initialize the network. It is recommended that the initialization of the synaptic weights of the network be uniformly distributed inside a small range. A range of -0.2 to +0.2 was used for random initialization of all synaptic weight vectors in the network.

Nonlinear Activation Function

The model of each neuron in the hidden layer(s) and output layer of the network includes a nonlinearity at the output end. The presence of a nonlinear activation function, φ(.), is important because otherwise the input-output relation of the network could be reduced to that of a single-layer perceptron. The computation of the local gradient for each neuron of the multilayer perceptron requires that the function φ(.) be continuous. In other words, differentiability is the only requirement that an activation function would need to satisfy.

For this problem, an asymmetric hyperbolic tangent function (tanh) was chosen for which the output amplitude lies inside the range $-1 \le y_j \le +1$. Since we require the final outputs to be real values instead of binary outputs, a linear combiner model was used for neurons in the output layer, thus omitting the nonlinear activation function.

Performance Measure (RMSE)

In order to track the performance of the network, the root mean squared error (RMSE) at the end of each epoch was calculated. An epoch is defined as one full presentation of all the training vectors to the network. The RMSE at the end of each epoch is defined as the following:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}\left[d_j - Y\left(X_j\right)\right]^2}{N}}$$

Where d_j is the desired response for the input training vector X_j, and N is the total number of input vectors presented to the network for training.

For the network to learn the problem smoothly, a monotonic decrease in the RMSE is expected with an increase in the number of epochs. A smooth learning curve was achieved with a learning-rate parameter (η) of 0.001.

ANN INPUTS AND OUTPUTS

Deflection basin parameters (DBPs) derived from falling weight deflectometer (FWD) and/or HWD deflection measurements are shown to be good indicators of selected pavement properties and conditions (Hossain and Zanniewski 1991). Recently, Xu et al. (2001) used DBPs in developing new relationships between selected pavement layer condition indicators and FWD deflections by applying regression and ANN techniques. Apart from the six independent deflection measurements (D_0 to D_{60}), some of the commonly used DBPs were included as inputs for training the ANN. The DBPs considered in this study are shown in Table 2. Each DBP supposedly represents the condition of specific pavement layers. For example, AUPP is sensitive to the asphalt concrete layer properties, whereas BCI and AI4 are expected to reflect the condition of subgrade. The desired outputs from the ANN are asphalt concrete modulus (E_{AC}), subgrade modulus (E_{Ri}), base modulus parameter (K_b or n_b), and subbase modulus parameter (K_s or n_s). Note that by predicting either K or n, the other parameter can be determined using the relation proposed by Rada and Witzcak (1981).

Table 2. DBPs considered in this study

Deflection basin parameter (DBP)	**Formula**
AREA	$AREA = 6(D_0 + 2D_{12} + 2D_{24} + D_{36})/D_0$
Area under pavement profile (AUPP)	$AUPP = (5D_0 - 2D_{12} - 2D_{24} - D_{36})/2$
Area index	$AI_4 = (D_{36} + D_{48})/2D_0$
Base curvature index (BCI)	$BCI = D_{24} - D_{36}$ $BCI2 = D_{60} - D_{48}$
Base damage index (BDI)	$BDI = D_{12} - D_{24}$
Deflection ratio	$DR = D_{12}/D_0$
Shape factors	$F_1 = (D_0 - D_{24})/D_{12}$ $F_2 = (D_{12} - D_{36})/D_{24}$

SELECTION OF BEST-PERFORMANCE NETWORKS

Separate ANN models were used for each desired output rather than using the same architecture to determine all the outputs together. The most effective set of input features for each ANN model were determined based on both engineering judgment and the experience gained through past research studies conducted at UIUC. Parametric analyses were performed by systematically varying the choice and number of inputs and number of hidden neurons to identify the best-performance networks. As it was found that the prediction accuracy of the network remained the same for hidden layers greater than or equal to two, the number of hidden layers was fixed at two for all runs. The learning curve (RMSE vs number of epochs) and the testing RMSE were studied in order to arrive at the best networks. A previous study that focused on the MFC section alone showed that the base and subbase moduli parameters were the hardest to predict (Gopalakrishnan and Thompson 2004). During the course of this study, the same conclusion was reached for other test sections. It was concluded that further research is needed to develop robust ANN models for predicting the base and subbase moduli parameters.

RESEARCH RESULTS

A summary of the sensitivity analyses performed to select the best-performance networks for predicting asphalt concrete modulus (E_{AC}) and subgrade modulus (E_{Ri}) in NAPTF test sections are shown in Table 3. Note that the ANN inputs are similar for all four test sections. In Figure 3, the ANN-predicted moduli values and the target values are compared using the 1,250 test data vectors for each NAPTF section. Excellent agreement is found between the predicted and target values for both E_{AC} and subgrade modulus E_{Ri} in all four test sections, except for E_{Ri} in LFS section, where an R^2 value of 0.81 was obtained.

Table 3. Summary of best-performance ANN pavement moduli prediction models

NAPTF section	Output	Inputs	Network architecture	Training RMSE	Testing RMSE
MFC	E_{AC}	$D_0 \sim D_{60}$	6-40-40-1	71 ksi	69 ksi
	E_{Ri}	$D_0 \sim D_{60}$, BCI, AI_4	8-40-40-1	0.86 ksi	0.82 ksi
LFC	E_{AC}	$D_0 \sim D_{60}$	6-40-40-1	100 ksi	97 ksi
	E_{Ri}	$D_0 \sim D_{60}$, BCI, AI_4	8-40-40-1	1.29 ksi	1.18 ksi
MFS	E_{AC}	$D_0 \sim D_{60}$	6-40-40-1	69 ksi	67 ksi
	E_{Ri}	$D_0 \sim D_{60}$, BCI, AI_4	8-40-40-1	0.81 ksi	0.78 ksi
LFS	E_{AC}	$D_0 \sim D_{60}$	6-40-40-1	90 ksi	90 ksi
	E_{Ri}	$D_0 \sim D_{60}$, BCI, AI_4	8-40-40-1	2.36 ksi	2.15 ksi

One of the major reasons for developing this ANN-based backcalculation procedure is to evaluate the structural integrity of the NAPTF pavement test sections reliably as they were subjected to traffic loading. The NAPTF test sections were subjected to trafficking until they exhibited failure. The MFC test section was the first one to fail at 12,952 load repetitions exhibiting 3 to 3.5 inches of rutting and severe cracking. In the MFS section, localized failure occurred in the Boeing 777 traffic lane toward the west end. At 19,900 passes, 3.5 inches of rut depth was observed on the Boeing 777 traffic lane, with upheaval outside the traffic path. Trafficking was terminated on the Boeing 777 traffic lane, but it continued on the Boeing 747 traffic lane. The Boeing 747 lane failed at 30,000 passes. HWD tests were not conducted on the MFS section beyond 19,900 passes. The low-strength test sections (LFC and LFS) showed few signs of genuine distress, even after 20,000 passes, and therefore the wheel loading was increased from 45,000 lbs to 65,000 lbs. The trafficking was terminated in the low-strength test sections after 28,000 passes of 65,000 lbs. While the MFC and MFS sections failed at the subgrade level, the LFC and LFS sections failed in the surface layers, signifying tire pressure or other upper layer failure effects, but not subgrade level failure (Gervais, Hayhoe, and Garg 2003).