

Backcalculation of Airport Flexible Pavement Non-Linear Moduli Using Artificial Neural Networks

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Abstract

The Heavy Weight Deflectometer (HWD) test is one of the most widely used tests for assessing the structural integrity of airport pavements in a non-destructive manner. The elastic moduli of the individual pavement layers “backcalculated” from the HWD deflection measurements are effective indicators of layer condition. Most of the backcalculation programs that are currently in use do not account for the non-linearity of unbound granular materials and fine-grained cohesive soils and therefore do not produce realistic results. The primary objective of this study was to develop a tool for backcalculating non-linear pavement layer moduli from HWD data using Artificial Neural Networks (ANN). A multi-layer, feed-forward network which 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, we were successfully able to predict the AC moduli and subgrade moduli. The final product was used in backcalculating pavement layer moduli from actual field data acquired at the National Airport Pavement Test Facility (NAPTF).

Introduction

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. In the case of airfields, a Heavy Weight Deflectometer (HWD) test, which is similar to a FWD test, but using higher load levels, is used. In an FWD/HWD 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 deflection of a pavement represents an overall “system response” of the pavement layers to an applied load. A conventional Asphalt Concrete (AC) pavement is typically made up of three layers: a surface layer paved with AC mix, a base or/and subbase layer made up of crushed stone, and a subgrade layer made up of natural soil. When a wheel load is applied on an AC pavement, the pavement layers deflect nearly vertically to form a basin as illustrated in Figure 1. The FWD/HWD

test tries to replicate the force history and deflection magnitudes of a moving truck tire/aircraft tire.

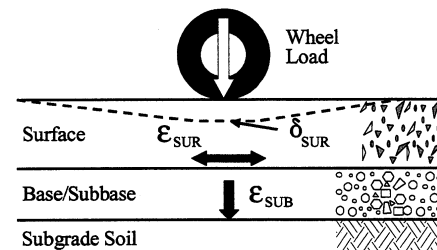


Figure 1. Illustration of Deflection Surface Caused by Moving Wheel Loads

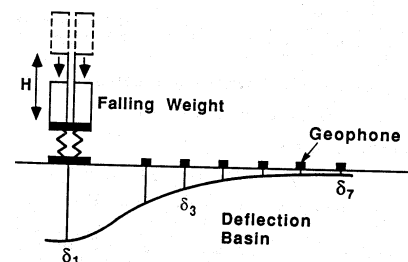


Figure 2. Schematic of FWD Load-Geophone Configuration and Deflection Basin

The deflected shape of the basin (Figure 2) is predominantly a function of the thickness of the pavement layers, the moduli of individual layers, and the magnitude of the load. “Backcalculation” is the accepted term used to identify a process whereby the elastic (Young’s) moduli of individual pavement layers are estimated based upon measured FWD/HWD surface deflections. As there are no closed-form solutions to accomplish this task, a mathematical model of the pavement system (called a forward model) is constructed and used to compute theoretical surface deflections with assumed initial layer moduli values at the appropriate FWD/HWD loads. Through a series of iterations, the layer moduli are changed, and the calculated deflections are then compared

to the measured deflections until a match is obtained within tolerance limits. Most of the commercial backcalculation programs currently in use (e.g. WESDEF, BISDEF) utilize an Elastic Layer Program (ELP) as the forward model to compute the surface deflections. For example, WESDEF uses WESLEA and BISDEF uses BISAR.

The ELPs consider the pavement as an elastic multi-layered media, and assume that pavement materials are linear-elastic, homogeneous and isotropic. However, in reality, it has been found that certain pavement materials do not show linear stress-strain relation under cyclic loading. The non-linearity or stress-dependency of resilient modulus for unbound granular materials and cohesive fine-grained subgrade soils is well documented in literature (Hicks 1970; Thompson and Robnett 1979). Unbound granular materials used in the base/subbase layer of an AC pavement show “stress-hardening” behavior (increase in resilient modulus with increasing hydrostatic stress) and cohesive subgrade soils show “stress-softening” behavior (reduction in resilient moduli with increased deviator stress). Therefore, the layer modulus is no longer a constant value, but a function of the stress state. Also, the ELPs do not account for the available shear strength of these unbound materials and frequently predict tensile stresses at the bottom of unbound granular layers which exceeds the available strength. Thus, the pavement layer moduli values predicted using ELP-based backcalculation programs are not very realistic.

ILLI-PAVE is a two-dimensional axi-symmetric pavement finite-element (FE) software developed at the University of Illinois at Urbana-Champaign (Raad and Figueroa 1980). It incorporates stress-sensitive material models and it provides a more realistic representation of the pavement structure and its response to loading. The primary objective of this study was to develop a tool for backcalculating non-linear pavement layer moduli from FWD/HWD data using Artificial Neural Networks (ANN). The reason for using ANN to accomplish this task is that once trained, they offer mathematical solutions that can be easily calculated in real-time on even the basic personal computers, unlike conventional backcalculation programs. Also, ANN can learn a backcalculation function that is based on much more realistic models of pavement response (e.g., ILLI-PAVE) than are used in traditional-basin matching programs. ANNs have been successfully used in the past for the backcalculation of flexible pavement moduli from FWD data (Meier and Rix 1993). However, they did not account for realistic pavement layer properties as ELP-generated synthetic database was used to train the ANN. Therefore, ILLI-PAVE was used in this study to develop the synthetic database which accounts for the nonlinearity in unbound material behavior. A multi-layer, feed-forward network which uses an error-backpropagation algorithm (LMS minimization) was trained to approximate the HWD backcalculation function. The final product was used in backcalculating pavement layer moduli from actual field data acquired at the National Airport Pavement Test Facility (NAPTF). The NAPTF was

constructed to generate full-scale testing data to support the investigation of the performance of airport pavements subjected to new generation aircrafts. The results from this study were compared with those obtained using a traditional ELP-based backcalculation program. It is noted that this is a preliminary study specifically targeted towards the backcalculation of pavement layer moduli from HWD data acquired at the NAPTF.

Database Generation Using ILLI-PAVE

A conventional airport flexible pavement section was modeled as a five-layered (AC layer, base layer, subbase layer, subgrade layer and a sand layer as constructed in conventional NAPTF test sections), two-dimensional, axisymmetric FE structure. A typical HWD test is performed by dropping a 36,000-lb load on the top of circular plate with a radius of 6 inches resting on the surface of the pavement. The loading duration is about 30 ms. Deflections are typically measured at offsets of 0-, 12-, 24-, 36-, 48- and 60-inches from the center of loading plate. The effect of HWD loading was simulated in ILLI-PAVE.

The AC 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:

$$M_R = \frac{\sigma_D}{\epsilon_R} = K\theta^n$$

Where M_R is resilient modulus (psi), θ is bulk stress (psi) and K and n are statistical parameters. Based on extensive testing of granular materials, Rada and Witzczak (1981) proposed the following relationship between K and n ($R^2 = 0.68$, SEE = 0.22):

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

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

$$M_R = M_{Ri} + K_1 \cdot (\sigma_d - \sigma_{di}) \quad \text{for } \sigma_d < \sigma_{di}$$

$$M_R = M_{Ri} + K_2 \cdot (\sigma_d - \sigma_{di}) \quad \text{for } \sigma_d > \sigma_{di}$$

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.

The thickness of the AC, base, subbase, subgrade and sand layers were held at constant values of 5, 8, 12, 95, and 120 inches respectively. These layer thicknesses are for a conventional AC pavement section (referred to as “MFC”) constructed at the NAPTF. The elastic modulus of the sand layer was fixed at 45,000 psi. Pavement surface deflections were computed at spacings of 0 (D_0), 12 (D_{12}), 24 (D_{24}), 36 (D_{36}), 48 (D_{48}), and 60 (D_{60}) inches from the load center.

Deflection Basin Parameters (DBPs) derived from FWD/HWD deflection measurements are shown to be

good indicators of selected pavement properties and conditions (Hossain and Zaniewski 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. The DBPs considered in this study are shown in Table 1. Each DBP supposedly represents the condition of specific pavement layers. For example, AUPP is sensitive to the AC layer properties whereas BCI and AI₄ are expected to reflect the condition of subgrade. Some of these DBPs were included as inputs for training the ANN apart from the 6 independent deflection measurements (D₀ to D₆).

Table 1. Deflection Basin Parameters (DBPs) Used in this Study

Deflection Basin Parameter (DBP)	Formula
Area Under Pavement Profile	$AUPP = (5D_0 - 2D_{12} - 2D_{24} - D_{36})/2$
Area Index	$AI_4 = (D_{36} + D_{48})/2D_0$
Base Curvature Index	$BCI = D_{24} - D_{36}$
Deflection Ratio	$DR = D_{12}/D_0$

A total of 5,000 data sets were generated by varying the AC and subgrade layer moduli, 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. Of the total number of data sets, 3,750 data vectors were used in training the ANN and the rest 1,250 data vectors were utilized for the testing the network after the training was completed. The range of layer properties used in training the ANN are summarized in Table 2.

In order for the network weights to compare the features to one another more easily, it is generally desirable to reduce each feature in the data set to zero mean and an approximately equal variance, usually unity. But, in this case, as the data was well controlled, all the features were reduced to similar orders of magnitude. Also, it is crucial that the training and test data both represent sampling from the same statistical distribution, which is also taken care of in this study.

Table 2. Range of Layer Properties Used to Train the ANN

Pavement Layer	Thickness (inches)	Elastic Layer Modulus (psi)
Asphalt Concrete	5	100,580 – 1,999,884
Base	8	K _b : 1,628 – 19,747 n _b : 0.2 – 0.8
Subbase	12	K _s : 1,628 – 19,750 n _s : 0.2 – 0.8
Subgrade	95	1,630 – 19,743
Sand	120	45,000

Network Architecture

A generalized *n*-layer feedforward artificial neural network which uses an error-backpropagation 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 in 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 layer 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.

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

To track the performance of the network a 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 defined as:

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

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. In order for the network to 'learn' the problem smoothly, a monotonic decrease in the RMSE is expected with increase in the number of epochs.

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 the University of Illinois. 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 range of (-0.2, +0.2) was used for random initialization of all synaptic weight vectors in the network. For this problem, an *asymmetric hyperbolic tangent* function (tanh) was chosen as the nonlinear activation function at the output end of all hidden neurons. Since, the final outputs (layer moduli) are real values rather than binary outputs, a *linear combiner* model was used for neurons in the output layer, thus omitting the nonlinear activation function. A smooth learning curve was achieved with a learning-rate parameter of 0.001.

Discussion of Results

The training progresses of the best-performance networks are captured in Figures 3-5. Table 3 summarizes the best-performance network architectures defined by the input features, the desired output and their prediction performance. The base and the subbase layer moduli were the hardest to predict. The difficulty associated with backcalculating the base/subbase layer modulus, especially if a thin AC layer is used, is a well recognized problem. It is sufficient to predict either 'n' or 'K' as there is a relation between the two. Note that the AC modulus (E_{AC}) predicted using the best ANN model is one of the inputs for predicting n_b . The RMSEs are significantly higher for both n_b and n_s . Therefore, the accuracy of predicting base and subbase layer moduli from HWD data using ANN is considered poor in this study. Figures 6 and 7 compare the target and ANN-predicted moduli of the AC and subgrade layers, respectively for the 1,250 test data vectors. The results are not shown for n_b and n_s as the R^2 values were poor. Excellent agreement is found between the target and ANN-predicted layer moduli for AC and subgrade layers. These two ANN models have successfully learned the backcalculation function over the entire range of pavement properties included in the training dataset.

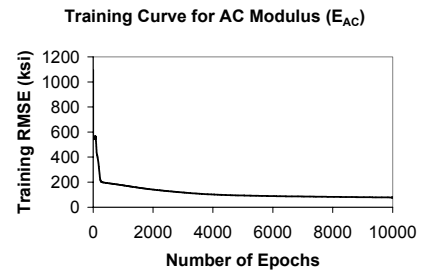


Figure 3. Training Curve for AC Modulus

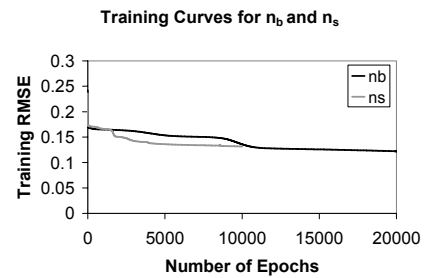


Figure 4. Training Curves for n_b and n_s

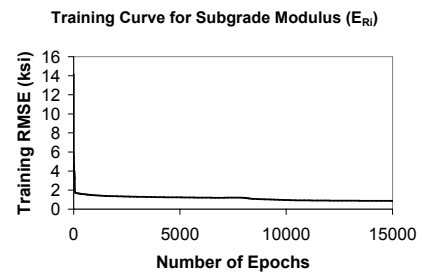


Figure 5. Training Curve for Subgrade Modulus

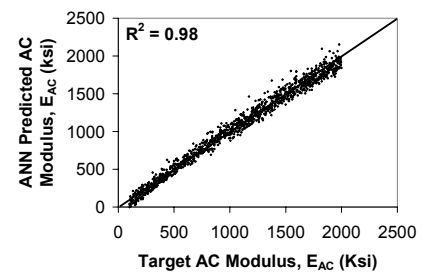


Figure 6. Prediction of AC Modulus

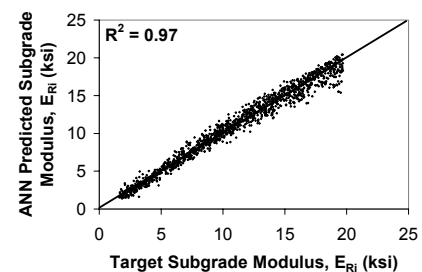


Figure 7. Prediction of Subgrade Modulus

Table 3. Summary of Best-Performance ANNs

Output	Inputs	Network Architecture	Testing RMSE
E_{ac}	$D_0 - D_{60}$	6-40-40-1	69.5 ksi
E_{ri}	$D_0 - D_{60}$, BCI, AI_4	8-40-40-1	0.82 ksi
n_b	$D_0 - D_{60}$, AUPP, E_{ac} , D_{12}/D_0	9-10-1	0.125
n_s	$D_0 - D_{60}$, E_{ac} , E_{ri}	8-40-40-1	0.136

ANN Application to Field Data

One of the major reasons for developing this backcalculation procedure is to reliably evaluate the structural integrity of the NAPTF pavement test sections as they were subjected to traffic loading. The NAPTF is located at the Federal Aviation Administration (FAA) William J. Hughes Technical Center, Atlantic City International Airport, New Jersey. The NAPTF test pavement area is 900-foot long and 60-foot wide and it includes six AC pavement sections. One of them is a conventional-base AC pavement built over a medium-strength subgrade which was modeled in this study. This test section is referred to as the “MFC”. All the pavement sections were subjected to a six-wheel tridem aircraft landing gear (Boeing 777) in one lane and a four-wheel tandem landing gear (Boeing 747) in the other lane simultaneously. The wheel loads were set at 45,000 lbs and the speed was 5 mph during trafficking. The test sections were trafficked to “failure”. According to the NAPTF failure criterion, pavements were considered to be failed when there is a 1-inch surface upheaval adjacent to the traffic lane. 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.

During the NAPTF traffic test program, HWD tests were conducted at various times to monitor the effect of time and traffic on the structural condition of the pavement. Tests were conducted on B777 traffic lane, B747 traffic lane and on the no-traffic Centerline (C/L). Using the HWD test data acquired at the NAPTF for the MFC test section, the AC moduli and subgrade moduli were backcalculated with the best-performance ANNs. The results were then compared with those obtained using FAABACKCAL, an ELP-based backcalculation program. FAABACKCAL was developed under the sponsorship of the FAA Airport Technology Branch and is based on the LEAF layered elastic computation program. A stiff layer with a modulus of 1,000,000 psi and a poisson’s ratio of 0.50 was used in backcalculation process. The plots comparing the results of ANN-based approach with those of FAABACKCAL are shown in Figure 8 for AC modulus and in Figure 9 for subgrade modulus.

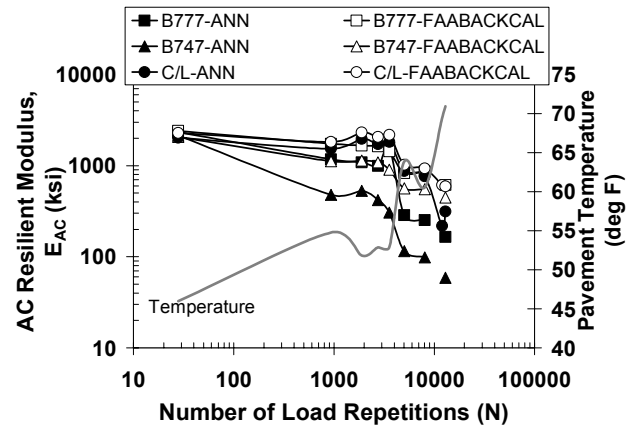


Figure 8. Comparison of ANN-predicted AC Moduli with FAABACKCAL AC Moduli (Field Data)

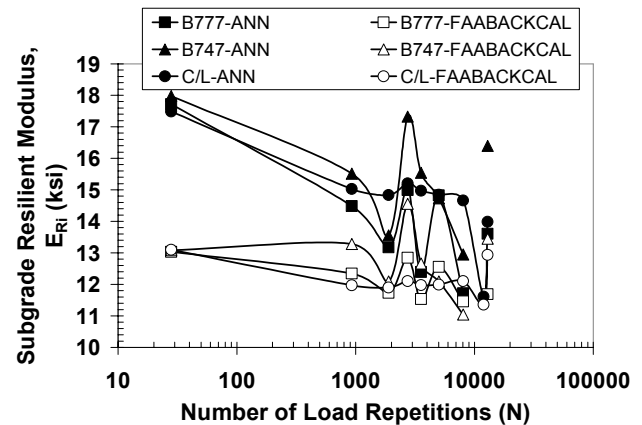


Figure 9. Comparison of ANN-predicted Subgrade Moduli with FAABACKCAL Subgrade Moduli (Field Data)

In the Figures, “B777-” and “B747-” in the legend refer to B777 traffic lane and B747 traffic lane respectively. One of the objectives of the NAPTF traffic test program was to compare the damaging effect of B777 and B747 landing gears on airport pavements. In these Figures, the changes in layer moduli in B777 traffic lane and B747 traffic lane are due to both traffic loading as well as variation in temperature and climate. The changes in pavement material properties in the pavement Centerline (C/L) are only due to environmental effects as the C/L was not subjected to trafficking.

In Figure 8, the variation in pavement temperature over the duration of trafficking program is indicated. Studies have shown that the AC modulus is very sensitive to pavement temperature. Therefore, the pavement temperature is plotted as well in Figure 8 on the secondary Y-axis. The AC modulus Vs N trend is similar for both ANN-predicted and FAABACKCAL results. The ANN-model seems to be more sensitive to traffic loading effects and temperature effects which is reflected in the sharp decrease in AC moduli with rise in temperature and

number of load repetitions. The B747 traffic lane is slightly more distressed in terms of reduction in elastic moduli compared to the B777 traffic lane. This is captured by the ANN-model. This result was confirmed by the NAPTF rutting study results (Gopalakrishnan and Thompson 2003). The NAPTF trench study results showed that the subgrade layer contributed significantly to the total pavement rutting in the MFC test section. The ANN-model shows an overall decreasing trend in subgrade moduli with increasing number of load repetitions, whereas the moduli values backcalculated using FAABACKCAL remain more or less the same throughout the trafficking program (see Figure 9).

Summary

The Heavy Weight Deflectometer (HWD) test is one of the most widely used tests for assessing the structural integrity of airport pavements in a non-destructive manner. In this 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. Backcalculation is the accepted term used to identify a process whereby the elastic (Young's) moduli of individual pavement layers are estimated based upon measured HWD surface deflections. The elastic moduli of the individual pavement layers are effective indicators of layer condition. They are also necessary inputs to mechanistic-based analysis and design of pavements. The ELP-based backcalculation programs do not account for the stress-dependency of unbound granular materials (used in the base and subbase layers) and fine-grained cohesive soils (used in the subgrade layer) and therefore do not produce realistic results. ILLI-PAVE is a pavement finite-element software that incorporates stress-sensitive material models and it provides a more realistic representation of the pavement structure and its response to loading. The primary objective of this study was to develop a tool for backcalculating non-linear pavement layer moduli from FWD/HWD data using Artificial Neural Networks (ANN). A multi-layer, feed-forward network which uses an error-backpropagation algorithm was trained to approximate the HWD backcalculation function. The ILLI-PAVE generated synthetic database was used to train the ANN. Using the ANN, we were successfully able to predict the AC moduli and subgrade moduli. The final product was used in backcalculating pavement layer moduli from actual field data acquired at the National Airport Pavement Test Facility (NAPTF). Although this is a preliminary study with a narrow scope, the results are very encouraging. Future studies would incorporate a wide range of pavement layer properties in the training dataset which would improve the generalization capabilities of the ANN. They would consider all four (two conventional-base and two asphalt-stabilized base) flexible test sections constructed at the NAPTF. The results would be used in

studying the comparative effect of B777 and B747 gears on the moduli values.

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