Rapid Finite-Element Based Airport Pavement Moduli Solutions using Neural Networks

Kasthurirangan Gopalakrishnan, Marshall R. Thompson, and Anshu Manik

***Abstract*—**This paper describes the use of artificial neural networks (ANN) for predicting non-linear layer moduli of flexible airfield pavements subjected to new generation aircraft (NGA) loading, based on the deflection profiles obtained from Heavy Weight Deflectometer (HWD) test data. The HWD test is one of the most widely used tests for routinely 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 profiles are effective indicators of layer condition and are used for estimating the pavement remaining life. HWD tests were periodically conducted at the Federal Aviation Administration's (FAA's) National Airport Pavement Test Facility (NAPTF) to monitor the effect of Boeing 777 (B777) and Beoing 747 (B747) test gear trafficking on the structural condition of flexible pavement sections. In this study, 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 an advanced non-linear pavement finite-element program was used to train the ANN to overcome the limitations associated with conventional pavement moduli backcalculation. The changes in ANN-based backcalculated pavement moduli with trafficking were used to compare the relative severity effects of the aircraft landing gears on the NAPTF test pavements.

***Keywords*—**Airfield pavements, ANN, backcalculation, new generation aircraft

I. 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 granular base or/and subbase layer made up of crushed stone, and a subgrade layer made up of soil. When a wheel load is applied on an AC pavement, the pavement layers deflect nearly vertically to form a basin as illustrated in Fig. 1. The FWD/HWD test tries to replicate the force history and deflection magnitudes of a moving truck tire/aircraft tire.

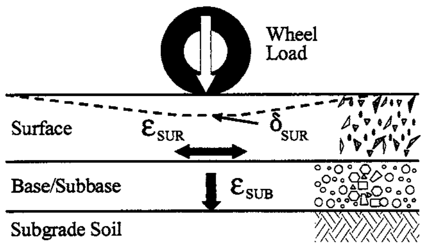

Fig. 1 Illustration of deflection surface caused by moving wheel loads

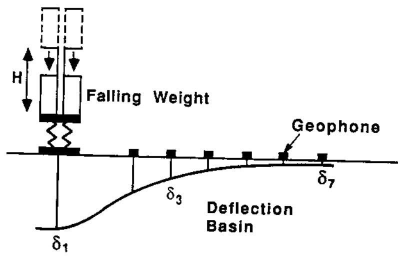

Fig. 2 Schematic of FWD configuration and deflection basin

The deflected shape of the basin (Fig. 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,

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and the calculated deflections are then compared to the measured deflections until a match is obtained within tolerance limits. Most of the conventional 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 [1]-[2]. 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 modulus with increasing 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 [3]. 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 airfield flexible pavement layer moduli from 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.

In recent years, ANNs are increasingly being used to solve pavement engineering problems which deal with highly non-linear functional approximations. In a study conducted at the University of Illinois, Ceylan [4] employed ANNs in the analysis of concrete pavement systems and developed ANN-based design tools that incorporated the state-of-the-art finite element solutions into routine practical design at several orders of magnitude faster than those sophisticated finite element programs. Several other studies have reported the development of similar ANN applications [5]-[8]. In the development of the new mechanistic-empirical pavement design guide for the American Association of State Highway and Transportation Officials (AASHTO), ANNs have been recognized as nontraditional, yet very powerful computing techniques and were employed in preparing the concrete pavement analysis package of the design guide.

ANNs have been successfully used in the past for the backcalculation of flexible pavement moduli from FWD data [9]. However, they did not account for realistic pavement layer properties as ELP-generated synthetic database was used to train the ANN. Recent studies at the Iowa State University and University of Illinois have focused on the development of ANN based models, trained using ILLI-PAVE generated synthetic database, to predict critical pavement responses and layer moduli from highway pavement FWD data [10].

The current study described in this paper focused on developing an effective tool for real-time backcalculation of flexible airfield pavement layer moduli based on Heavy Weight Deflectometer (HWD) test data. A multi-layer, feed-forward network which uses an error-backpropagation algorithm was trained to approximate the HWD backcalculation function. The developed ANN-models were used in backcalculating pavement layer moduli from actual HWD test 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 aircraft. The NAPTF test details are discussed under a separate section.

The results from this study were also compared with those obtained using a conventional ELP-based backcalculation program. It is noted that this was an initial study with limited scope specifically targeted towards the backcalculation of pavement layer moduli from HWD data acquired at the NAPTF. However, the results highlight the potential for extending this concept for developing generic ANN-based models which would be useful in the analysis of routine HWD test data collected at flexible airfield pavements. This could be accomplished by training the ANN models developed in this study over a broad range of input values.

II. The National Airport Pavement Test Facility

A. Pavement Test Sections

The NAPTF is located at the Federal Aviation Administration's (FAA's) William J. Hughes Technical Center, Atlantic City International Airport, New Jersey. The NAPTF test pavement area is 274-m (900-ft) long and 18.3-m (60-ft) wide. Due to space constraints, the results for the following two flexible pavement sections are discussed in this paper: (a) *LFC*-a conventional granular base flexible pavement section built over a low-strength subgrade; and (b) *LFS*-an asphalt-stabilized base flexible pavement section built over a low-strength subgrade. Cross-sectional views of the as-constructed NAPTF flexible test sections are shown in Fig. 2.

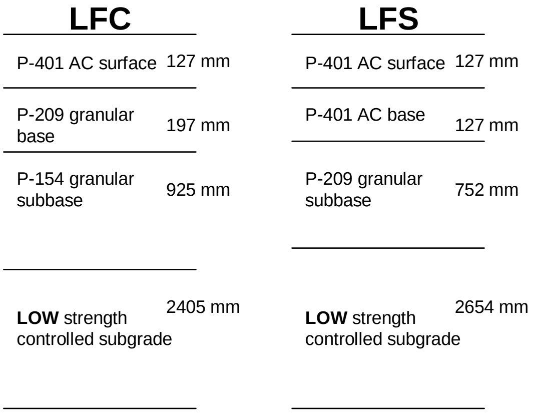

Fig.3 Cross-sectional views of NAPTF test sections

The items P-209, P-154 and P-401 are as per standard specifications detailed in the FAA Circular No. AC 150/5370-10A. A CL-CH soil classification (ASTM Unified Soil Classification System) material known as Dupont Clay (DPC) was used for the low-strength subgrade. The naturally-occurring sandy-soil material (SW-SM soil classification) at the NAPTF site underlies each subgrade layer. The gradation information as well as the laboratory compaction properties for the subgrade soils, P-209 crushed stone base, and P-154 subbase (stone screenings) are presented elsewhere [11].

B. Traffic Testing

A six-wheel dual-tridem gear configuration with 1,372-mm (54-in.) dual spacing and 1,448-mm (57-in.) tandem spacing, representative of Boeing-777 (B777) landing gear, was loaded on the north side wheel track. The south side was loaded with a four-wheel Boeing-747 (B747) dual-tandem gear configuration having 1,118-mm (44-in.) dual spacing and 1,473-mm (58-in.) tandem spacing. The wheel loads were set to 20.4 tonnes (45,000-lbs) each and the tire pressure (cold) was 1,295 kPa (188 psi). In the LFC and LFS test sections, the wheel loads were increased from 20.4 tonnes (45,000-lbs) to 29.4 tonnes (65,000-lbs) after 20,000 initial load repetitions. Throughout the traffic test program, the traffic speed was 8 km/h (5 mph). The NAPTF test sections were trafficked until they exhibited 25.4-mm (1-in.) surface upheaval adjacent to the traffic lane, as per NAPTF failure criterion.

C. HWD Tests

At NAPTF, the HWD tests were conducted at specified intervals throughout the traffic testing to monitor the effect of trafficking on the structural condition of the pavements. A typical HWD test is performed by dropping a load on the top of circular plate with a specified radius resting on the surface of the pavement. For NAPTF HWD tests, a 160-kN (36,000-lb) load, a 30-cm (12-in.) loading plate and a 27-30 msec pulse width were used. The deflections were measured with six geophones at offsets of 0 (D_0), 305 mm (D_1), 610 mm (D_2), 914 mm (D_3), 1219 mm (D_4), and 1524 mm (D_5) intervals from the center of the load. The tests were performed on the centerline (C/L), B777 traffic lane and B747 traffic lane. The HWD test sequences were repeated at 3-m (10-ft) intervals along the test lanes. The location and orientation of HWD test lanes are illustrated in Fig. 4 along with the traffic test gear configurations.

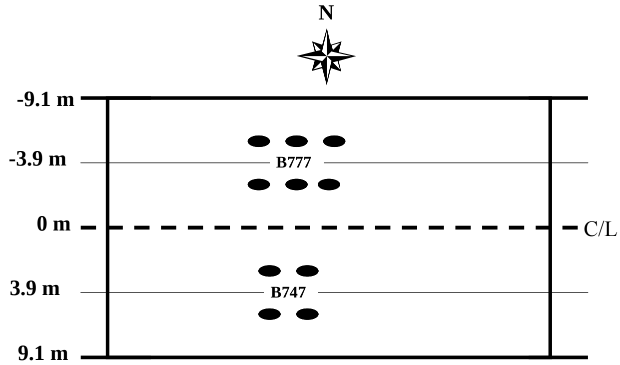

Fig. 4 HWD test lanes

III. GENERATION OF TRAINING AND TESTING DATABASE

The NAPTF flexible test sections were separately modeled as two-dimensional, axisymmetric FE structures using the as-constructed layer thicknesses. The individual pavement layers were characterized as follow.

The AC surface layer and the natural sand layer beneath the subgrade were characterized as a 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:

$$E_R = \frac{\sigma_D}{\varepsilon_R} = K\theta^n \quad (1)$$

where E_R is resilient modulus (kPa), θ is bulk stress (kPa) and K and n are statistical parameters. It has been shown that an inverse relationship exists between K and n [12].

The fine-grained low-strength subgrade was modeled using the bi-linear model for characterizing the resilient modulus:

$$\begin{aligned} E_R &= E_{Ri} + K_1.(\sigma_d - \sigma_{di}) \quad \textit{for } \sigma_d < \sigma_{di} \\ E_R &= E_{Ri} + K_2.(\sigma_d - \sigma_{di}) \quad \textit{for } \sigma_d > \sigma_{di} \end{aligned} \quad (2)$$

where E_R is resilient modulus (kPa), σ_d is applied deviator stress (kPa), and K_1 and K_2 are statistically determined coefficients from laboratory tests.

The bi-linear model [13] is a commonly used resilient modulus model for subgrade soils. The value of the resilient modulus at the breakpoint in the bi-linear model, E_{Ri}, can be used to classify fine-grained soils as being soft, medium or stiff.

The effect of 160-kN (36,000-lb) HWD loading was simulated in ILLI-PAVE. A total of 5,000 datasets were generated for each test section by randomly varying the layer moduli parameters over typical ranges. During the initial phase, it was decided to use separate ANN models for each section. Of the total number of data sets, 3,750 data vectors were used in training the ANN and the remaining 1,250 data vectors were utilized for the testing the network after the training was completed. The ranges of layer properties used in training the ANN are summarized in Table 1.

TABLE I
RANGE OF LAYER PROPERTIES

Pavement Layer	Thickness (mm)	Layer modulus (MPa)	Poisson's ratio
P-401 Asphalt Concrete (AC)	LFC - 127 LFS - 254	690 – 18,000	0.35
P-209 Base	LFC – 197	K: 11 – 140 n: 0.2 – 0.8	0.35
P-209 Subbase	LFC – 925 LFS – 752	K: 11 – 140 n: 0.2 – 0.8	0.35
Subgrade	LFC – 2,405 LFS – 2,654	11 – 140	0.45
Sand	3,660	310	0.4

IV. ANN Architecture

A generalized n-layer feedforward artificial neural network which uses an error backpropagation (BP) training algorithm [14] was implemented. The BP algorithm is based on a gradient-descent optimization technique and is now described in many textbooks [15]. BP networks excel at data modeling with their superior function approximation capabilities [16] and a great majority of civil engineering application of neural networks is based on the use of the BP algorithm primarily because of its simplicity [17].

The BP model developed in this study 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. 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).

The first step in back-propagation 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, +0.2) was used for random initialization of all synaptic weight vectors in the network for this study.

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 have to satisfy.

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

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 defined as:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}\left[d_j - Y\left(X_j\right)\right]^2}{N}} \tag{3}$$

where d_j is the desired response for the input training vector X_j, $Y(X_j)$ is the computed output, 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 increase in the number of epochs. A smooth learning curve was achieved with a learning-rate parameter (η) of 0.001.

V. ANN inputs and outputs

Deflection Basin Parameters (DBPs) derived from FWD/HWD deflection measurements are shown to be good indicators of selected pavement properties and conditions [18]. Recently, Xu et al [19] 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_5), some of the commonly used DBPs were included as inputs for training the ANN (see Table II).

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. The desired outputs from the ANN are: AC 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 [12].

VI. 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 past experience gained through 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.

TABLE II
Range of Layer Properties

Deflection Basin Parameter (DBP)	Formula
AREA	$AREA = 6(D_0 + 2D_1 + 2D_2 + D_3)/D_0$
Area Under Pavement Profile (AUPP)	$AUPP = (5D_0 - 2D_1 - 2D_2 - D_3)/2$
Area Index	$AI_4 = (D_3 + D_4)/2D_0$
Base Curvature Index (BCI)	$BCI = D_2 - D_3$ $BCI2 = D_5 - D_4$
Base Damage Index (BDI)	$BDI = D_1 - D_2$
Deflection Ratio	$DR = D_1/D_0$

The learning curve (RMSE Vs number of epochs) and the testing RMSE were studied in order to arrive at the best networks. It was found that the base and subbase moduli parameters (K and n) were the hardest to predict. Further research is needed to develop robust ANN models for predicting the non-linear base and subbase moduli parameters.

VII. ANN Prediction of Pavement Moduli

A summary of the sensitivity analyses performed to select the best-performance networks for predicting AC modulus (E_{AC}) and subgrade modulus (E_{Ri}) in NAPTF test sections are shown in Table III. Note that the ANN inputs are similar for both the test sections. In general, the testing RMSEs for the two output variables were slightly lower than the training ones. In Fig. 5 to Fig. 8, the ANN-predicted pavement layer moduli values and the ILLI-PAVE target values are compared using the 1,250 test data vectors. Due to space constraints, results are displayed only for the LFC test section. Similar results were obtained for the LFS section. Average Absolute Errors (AAEs), calculated as sum of the individual absolute errors divided by the 1,250 independent testing patterns, are also reported in the figures. Excellent agreement is found between the predicted and target values for both E_{AC} and subgrade modulus E_{Ri}.

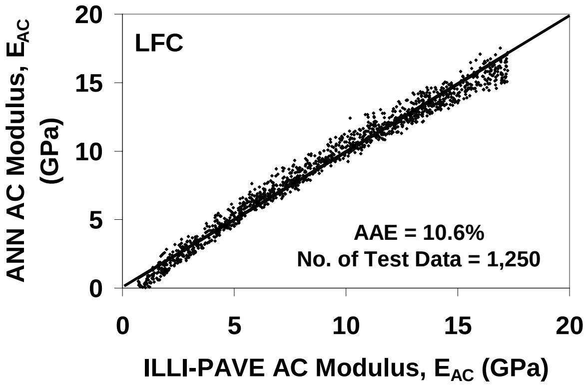

Fig. 5 ANN prediction of AC modulus (E_{AC})

TABLE III
Best Performance ANN Prediction Models

NAPTF Section	Output	Inputs	Network Architecture	Training RMSE	Testing RMSE
LFC	E_{AC}	D_0 to D_5	6-40-40-1	0.69 GPa	0.66 GPa
	E_{Ri}	D_0 to D_5, BCI, AI_4	8-40-40-1	8.9 MPa	8.1 MPa
LFS	E_{AC}	D_0 to D_5	6-40-40-1	0.62 GPa	0.62 GPa
	E_{Ri}	D_0 to D_5, BCI, AI_4	8-40-40-1	16 MPa	14.8 MPa

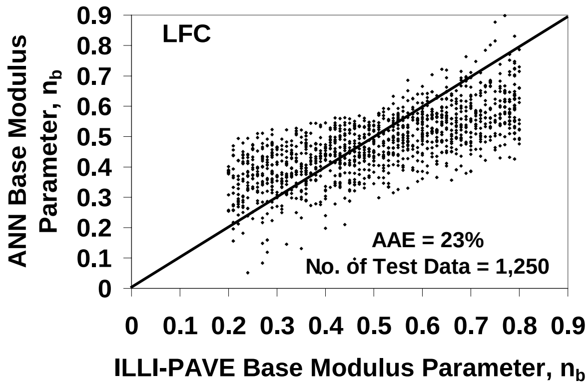

Fig. 6 ANN prediction of base modulus parameter (n_b)

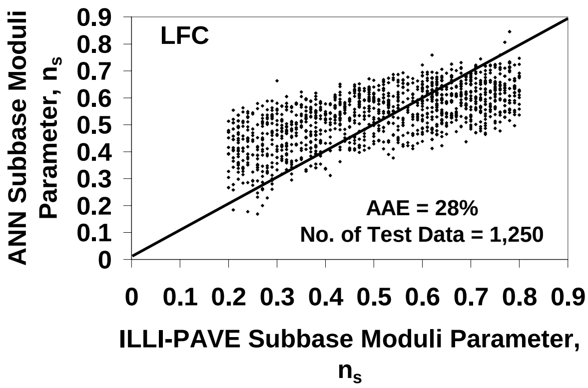

Fig. 7 ANN prediction of subbase modulus parameter (n_s)

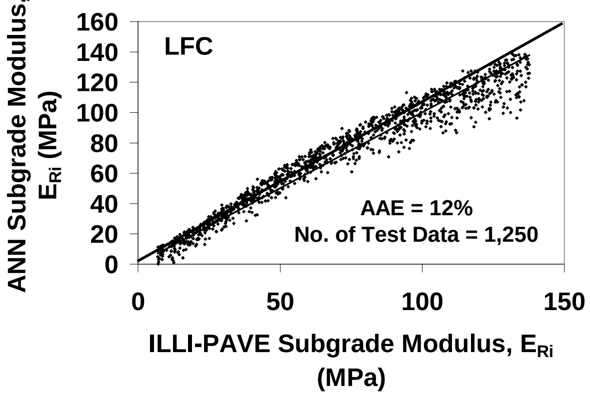

Fig. 8 ANN prediction of subgrade modulus (E_{Ri})

As mentioned previously, the base and subbase modulus parameters could not be predicted with reasonable accuracy.

One of the major reasons for developing this ANN-based moduli backcalculation procedure is to reliably evaluate the structural integrity of the NAPTF pavement test sections as they were subjected to traffic loading. The NAPTF test sections were subjected to trafficking until they exhibited failure (i.e., until they exhibited 25.4-mm surface upheaval adjacent to the traffic lane).

The LFC and LFS sections showed few signs of genuine distress even after 20,000 passes and therefore the wheel loading was increased from 20.4-ton (45,000-lb) to 29.4-ton (65,000-lb). The trafficking was terminated in the LFC and LFS test sections after 28,000 passes of 29.4-ton (65,000-lb) wheel load trafficking. The post-traffic trench studies revealed that the LFC and LFS sections failed in the surface layers, signifying tire pressure or other upper layer failure effects, but not subgrade level failure [20].

VIII. Effect of Trafficking on Pavement Moduli

To study the loss of stiffness in NAPTF flexible pavement sections resulting from trafficking, the AC and subgrade layer moduli values were backcalculated from the 160-kN (36-kip) HWD data acquired at the NAPTF using the ANN prediction models developed in this study.

The ANN predicted results were then compared with those obtained using a conventional modulus backcalculation program, BAKFAA which assumes the pavement materials to be linear elastic. The BAKFAA was developed under the sponsorship of the FAA Airport Technology Branch and is based on the LEAF layered elastic computation program [21]. In this program, the pavement layer moduli are adjusted to minimize the root mean square (rms) of the differences between FWD/HWD sensor measurements and the LEAF-computed deflection basin for a specified pavement structure. A standard multidimensional simplex optimization routine is then used to adjust the moduli values [22]. The detailed backcalculation results for NAPTF sections using the FAABACKCAL are reported elsewhere [11].

Note that the 160-kN (36-kip) HWD testing was performed at different stages during the trafficking on B777 traffic lane, B747 traffic lane and the untrafficked Centerline (C/L) of the test pavement (see Fig. 4). It is reasonable to assume that the variation in moduli values in the C/L is mainly due to climatic effects. Thus, the changes in AC and subgrade moduli values in the traffic lanes can be compared to the corresponding C/L values and the degree of structural deterioration induced by B777 trafficking and B747 trafficking can be assessed.

The variations in ANN predicted AC moduli (E_{AC}) values with the number of traffic load repetitions (N) are displayed in Fig. 9 and Fig. 10 for LFC and LFS test sections, respectively. The gray arrow in the plots for LFC and LFS sections indicate where (20,000 load repetitions) the wheel load was increased from 20.4-ton (45,000-lb) to 29.4-ton (65,000-lb). Note that the changes in E_{AC} values in the untrafficked C/L are mainly due to the changes in the AC temperature. As expected, E_{AC} is significantly influenced by changes in AC temperature.

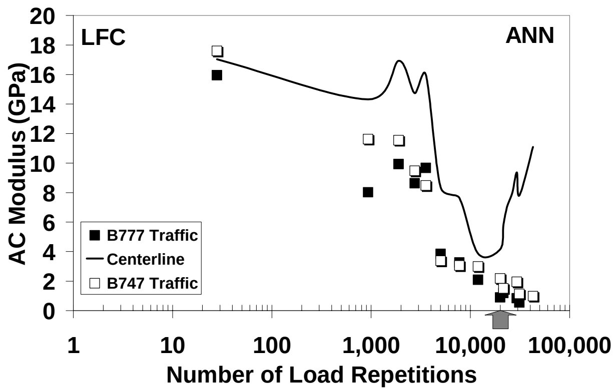

Fig. 9 ANN predicted AC modulus versus N (LFC)

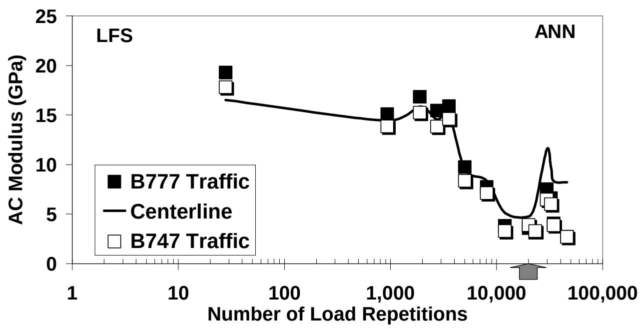

Fig. 10 ANN predicted AC modulus versus N (LFS)

In the plots, the untrafficked centerline (C/L) AC modulus values (E_{AC}) and the trafficked lane values remain close to each other until 20,000 passes. Note that the wheel load magnitude was increased from 20.4 tonnes to 29.4 tonnes after 20,000 load repetitions in LFC and LFS sections. After 20000 passes the trafficked lane values show significant decrease compared to the C/L values. This is especially true in the LFC test section. At approximately 12,000 passes under the 20.4-ton (45-kip) wheel loading, the C/L E_{AC} value is 3.8 GPa while it is approximately 2.1 GPa (55% of C/L value) in the

B777 traffic lane and is 3.0 GPa (79% of C/L value) in the B747 traffic lane. After 20,000 passes of 20.4-ton wheel loading and 12,000 passes of 29.4-ton (65-kip) wheel loading, the E_{AC} values are 7.8 GPa in the C/L, 0.6 GPa in the B777 traffic lane (8% of C/L value) and 1.1 GPa in the B747 traffic lane (14% of C/L value).

The effect of trafficking on ANN backcalculated subgrade modulus values (E_{Ri}) is captured in Fig. 11 and Fig. 12 for LFC and LFS sections respectively. In the plots, the Y-axis is magnified as the subgrade moduli varied over a narrow range compared to the AC moduli. Compared to the C/L E_{Ri} values, the traffic lane E_{Ri} values show reduction in magnitude in the LFC and LFS sections as trafficking progresses.

The HWD tests were conducted in the center of the B777 and B747 traffic paths in addition to the tests on the pavement C/L. As trafficking progressed, it is not known whether the HWD tests were conducted in the middle of the rutted area or towards the edges which showed surface upheaval. If the tests were conducted in the middle of the rutted areas (which were wide in extent) and not near the edge where subgrade shear occurred, a difference in backcalculated subgrade modulus may not result as a result of trafficking. In fact, a slight increase in subgrade modulus in the area tested may have occurred from compaction as seen in Fig. 11 towards the end of traffic testing.

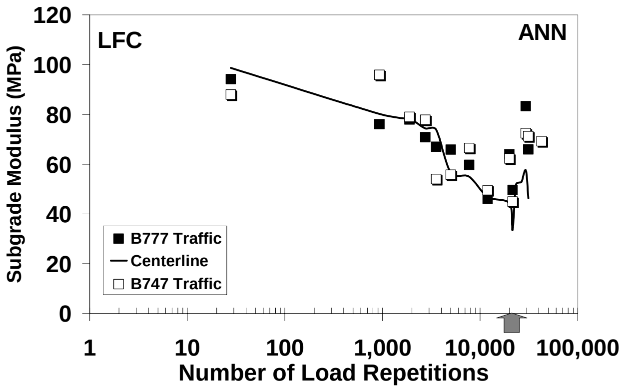

Fig. 11 ANN predicted subgrade modulus versus N (LFC)

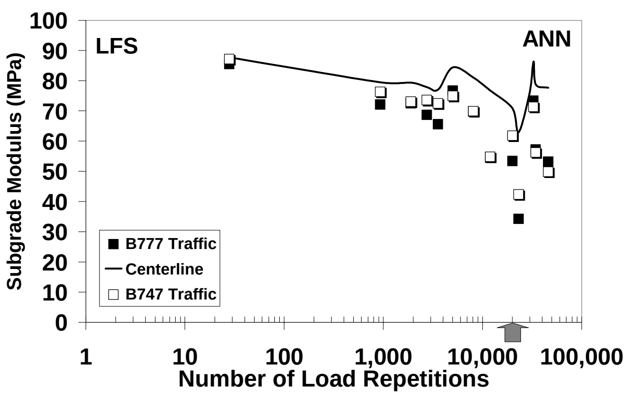

Fig. 12 ANN predicted subgrade modulus versus N (LFS)

It is observed from figures 9 to 12 that, from an engineering standpoint, the effect of B777 trafficking on AC and subgrade moduli is not significantly different from that effected by B747 trafficking. Thus, the damaging effect of B777 and B747 traffic gears on flexible airfield pavements can be considered to be approximately equivalent based on the results from this study.

The comparison between the ANN predicted moduli values and BAKFAA backcalculated moduli values are presented in Fig. 13 and Fig. 14 for AC modulus and subgrade modulus, respectively. It should be noted that the rut depths in the NAPTF flexible test sections reached significant levels (76 mm to 102 mm) towards the end of traffic testing and therefore the HWD test results and hence the backcalculated moduli values showed significant variability during the final stages of traffic testing.

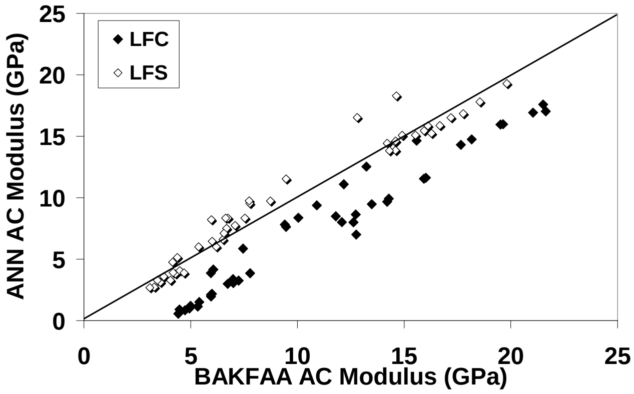

Fig. 13 ANN AC moduli predictions compared with BAKFAA predictions

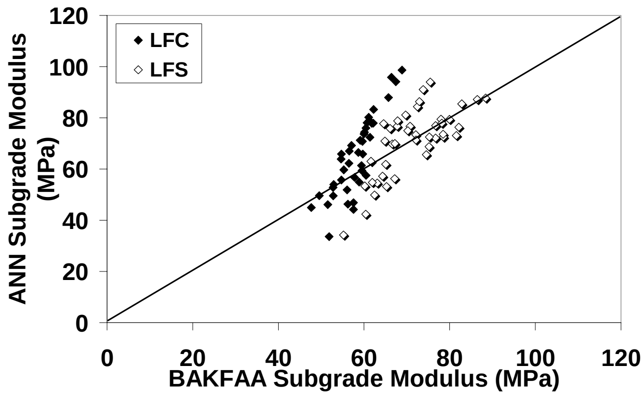

Fig. 14 ANN subgrade moduli predictions compared with BAKFAA predictions

It is seen that the ANN predicted AC moduli values agree well with the BAKFAA computed values for LFS section. In LFC section, the ANN predicted values are lower compared to the BAKFAA predicted values consistently. Similarly, there are variations between the ANN predicted subgrade modulus values and the BAKFAA computed values. Note that the ANN model predicts the stress-dependent subgrade breakpoint resilient modulus, E_{Ri}, whereas the subgrade modulus backcalculated by BAKFAA is based on the assumption that the subgrade soils are linear elastic. The differences in results between the two methodologies could also be attributed to the pavement structural model used in response computations. BAKFAA uses the LEAF multi-layered elastic analysis program whereas the ILLI-PAVE finite-element based program models the pavement as a 2D axisymmetric solid of revolution and employs nonlinear stress-dependent models and failure criteria for granular materials and fine-grained soils.

It is expected that the prediction of stress-dependent E_{Ri} would improve if multiple HWD load levels (53-kN, 107-kN, and 160-kN) are used in the generation of ILLI-PAVE synthetic database and in the development of the ANN algorithms. Further research is needed to develop robust ANN models for predicting base/subbase moduli parameters. It is proposed that by including the ANN-predicted E_{AC} and E_{Ri} values as inputs to the ANN, the chances of accurately predicting base/subbase moduli will increase. Also, the robustness of the ANN can be improved by including the field data sets in the training process, as they implicitly incorporate noise and errors seen typically in field measurements.

IX. Conclusion

The primary objective of this study was to develop an effective tool for real-time backcalculation of airport flexible pavement non-linear layer moduli from HWD data using Artificial Neural Networks (ANN), especially for airport flexible pavements serving the New-Generation Aircraft (NGA). The NAPTF sections were modeled in ILLI-PAVE and synthetic database was generated for a range of moduli values. A multi-layer, feed-forward network which uses an error-backpropagation algorithm was successfully trained to approximate the HWD backcalculation function using the ILLI-PAVE database. The ILLI-PAVE solutions database was used in the ANN training to account for the typical stress-hardening behavior of unbound granular materials and stress-softening behavior of fine-grained subgrade soils.

ANN surrogate models were successfully developed for predicting AC and non-linear subgrade moduli from actual HWD field test data. However, the base/subbase moduli could not be predicted using ANN. Such ANN-based rapid solutions can enable analysis of a large number of HWD pavement deflection basins in real time, needed for routine airfield pavement evaluation.

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