Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 6 (7): 1547-1552, 2006
ISSN 1812-5654

Prediction of Airport Flexible Pavement Critical Responses from Non-destructive Test Data Using ANN-based Structural Models

Kasthurirangan Gopalakrishnan
Department of Civil Engineering, Iowa State University,
498 Town Engineering Building, Ames, IA 50011-3232, USA

Abstract: This study describes the development of Artificial Neural Network (ANN) based pavement response prediction models for rapid structural analysis of airport flexible pavements based on Non-destructive Test (NDT) data. A finite element based pavement structural model, which can accommodate stress-sensitive geomaterial stiffness models, was used to generate the ANN training and testing dataset. The goal was to establish ANN models for predicting critical responses (stresses and strains) from routine NDT airfield pavement structural evaluation data. The developed ANN models predicted the critical pavement responses obtained from the finite element model with good accuracy. Further research is required to achieve increased prediction accuracies and validate the ANN models using actual field data.

Key words: Artificial Neural Networks (ANN), Heavy Weight Deflectometer (HWD), airport flexible pavement, critical pavement responses

INTRODUCTION

A conventional Asphalt Concrete (AC) pavement found in the USA is typically made up of three layers: a surface layer paved with AC mix, a base or/and subbase layer made up of granular material and a subgrade layer made up of natural soil. The conventional structural models (Elastic Layer Programs or ELPs) used in the AC pavement analysis 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 unbound granular materials and subgrade soils, referred to as pavement geomaterials, do not follow a 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). The resilient modulus (M_r) of the pavement materials is defined as the repeated applied wheel load stress divided by the recoverable strain.

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) (Hicks, 1970; Thompson and Robnett, 1979). 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. Pavement structural models that can realistically predict the critical responses are required for reliable mechanistic based pavement design.

ILLI-PAVE is a two-dimensional axi-symmetric flexible pavement finite-element (FE) structural model (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. In this study, ILLI-PAVE generated synthetic database was used to train and test Artificial Neural Network (ANN) based structural models developed for real-time and accurate structural analysis of flexible airfield pavements.

Approach: The goal was to establish ANN models for predicting critical responses (stresses and strains) from routine non-destructive airfield pavement structural evaluation data. 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. The FWD/HWD test tries to replicate the force history and deflection magnitudes of a moving truck tire/aircraft tire.

In this study, ANN-based models were developed to predict critical structural responses from realistic HWD deflection basins. A significant benefit of using such validated ANN-based models in routine pavement analysis and design is that they provide the same sophistication as time-consuming finite element modeling (e.g., ILLI-PAVE) required for realistic characterization of pavement layers, but at the same time provide almost instantaneous results.

Recent research studies at the Iowa State University and University of Illinois in the USA have focused on the development of ANN based flexible pavement analysis models to predict critical pavement responses and layer moduli (Ceylan *et al*., 2004). Researchers have successfully 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 (Ceylan *et al*., 2004).

The current study described in this research focused on the development of ANN-based models for the rapid structural analysis of airport flexible pavements subjected to new-generation, heavy aircrafts such as Boeing B-777. A multi-layer, feed-forward network which uses an error-backpropagation algorithm was trained to predict critical structural responses from the HWD deflection basins. The goal was to use the ANN-prediction models for analyzing the airport flexible pavement sections at the Federal Aviation Administration's (FAA) National Airport Pavement Test Facility (NAPTF). The NAPTF is a state-of-the-art full-scale test facility constructed to generate test data to support the development of advanced airport pavement design procedures.

Generation of training vectors: A conventional airport flexible pavement section, built at NAPTF, was modeled as a five-layered (AC, base, subbase and subgrade layers resting on locally available sand), two-dimensional, axisymmetric FE structure. A typical HWD test is performed by dropping a 160 kN (36,000 lb) load on the top of circular plate with a radius of 152 mm (6 in) resting on the surface of the pavement. The loading duration is about 30 ms. Deflections are typically measured at offsets of 0 mm (D_0), 254 mm (D_1), 610 mm (D_2), 914 mm (D_3), 1219 mm (D_4) and 1524 mm (D_5) from the center of loading plate. The effect of HWD loading was simulated in ILLI-PAVE.

The AC layer and the sand layer were modeled as linear elastic material. Stress-dependent elastic models along with Mohr-Coulomb failure criteria were applied for the unbound base, subbase and subgrade layers. The stress-hardening K-θ model (Hicks and Monismith, 1971) 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, θ is bulk stress and K and n are statistical regression parameters. Note that higher values of K and lower values of n apply to good quality materials like crushed stone. An inverse relationship exists between K and n (Rada and Witczak, 1981) such that by knowing one parameter, the other can be determined.

The arithmetic bilinear model (Thompson and Robnett, 1979) was used for the subgrade layer:

$$\begin{aligned} M_R &= M_{Ri}+K_1.(\sigma_d-\sigma_{di}) \text{ for } \sigma_d<\sigma_{di} \\ M_R &= M_{Ri}+K_2.(\sigma_d-\sigma_{di}) \text{ for } \sigma_d>\sigma_{di} \end{aligned} \tag{2}$$

Where M_R is resilient modulus, σ_d is applied deviator stress and K_1 and K_2 are statistically determined coefficients from laboratory tests. The value of resilient modulus at the breakpoint in the bilinear curve, M_{Ri}, can be used to classify fine-grained subgrade soils as being soft, medium or stiff.

The thickness of the AC, base, subbase and subgrade layers were held at constant values of 127 mm (5 in.), 200 mm (7.9 in.), 307 mm (12.1 in.) and 2405 mm (94.7 in.). 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 310 MPa (45,000 psi). Apart from the surface deflections, the strains at the bottom of the AC layer (ε_{AC}) and on top of the subgrade (ε_{SG}), major and minor stresses (σ_1 and σ_3) and deviatoric stress on top of subgrade (σ_D) were also computed. The importance of these parameters in the context of airport flexible pavement analysis and design is discussed later.

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, DBPs were used in developing new relationships between selected pavement layer condition indicators and FWD deflections by applying regression and ANN techniques (Xu *et al*., 2001). The DBPs considered in the current study are shown in Table 1. Some of these DBPs were included as inputs for training the ANN apart from the six independent HWD deflection measurements (D_0 to D_5).

Table 1: Deflection Basin Parameters (DBPs) considered in this study

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	$DR = D_1/D_0$
Shape factors	$F_1 = (D_0-D_2)/D_1$
	$F_2 = (D_{12}-D_3)/D_2$

Table 2: Range of layer properties used to train the ANN

Pavement layer	Thickness (mm)	Elastic Layer Modulus (MPa)	Poisson's ratio
Asphalt concrete	127	690-14,000	0.35
Base	200	K_b: 11-140	0.35
Subbase	307	K_s: 11-140	0.35
Subgrade	2405	11-140	0.45
Sand	3048	310	0.4

A total of 5,000 data sets were generated by varying the AC and subgrade layer moduli, the magnitudes of K_b-n_b and K_s-n_s parameters (note that K and n are related inversely) 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 remaining 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.

Artificial neural network architecture: A generalized n-layer feedforward artificial neural network which uses an error-backpropagation algorithm was implemented in this study (Gopalakrishnan, 2004). Backpropagation neural networks are very powerful and versatile neural networks which excel at data modeling with their superior function approximation capabilities (Haykin, 1999).

The backpropagation ANN-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 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 has 10 input nodes, has 2 hidden layers consisting of 40 neurons each and 3 output nodes.

Using the ILLI-PAVE synthetic database, the ANN was trained to learn the relation between the synthetic deflection basins (inputs) and the critical pavement responses. 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:

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

where d_j is the desired response for the input training vector X_j, $Y(X_j)$ is the ANN predicted response for the input 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. The learning curve (RMSE Vs number of epochs) and the testing RMSE were studied in order to arrive at the best networks.

ANN prediction of critical pavement responses: Some of the most common inputs for mechanistic analysis of airport flexible pavement performance include:

- ε_{AC}, tensile strain at the bottom of the AC layer,
- ε_{SG}, vertical compressive strain on top of the subgrade and
- σ_d, deviator stress on top of the subgrade (used to calculate the Subgrade Stress Ratio [SSR])

In the context of routine structural evaluation of in-service pavements, these critical responses, determined from the FWD/HWD test data, serve as indirect layer condition indicators and could be used to predict the remaining life of the pavements. Distress modes normally considered in flexible pavement analysis and design are AC fatigue cracking and rutting (Thompson and Nauman, 1993). Airport flexible pavement design procedures limit the vertical compressive strain on top of the subgrade (subgrade rutting failure criteria) and the tensile strain at the bottom of the lowest AC layer (AC fatigue failure criteria).

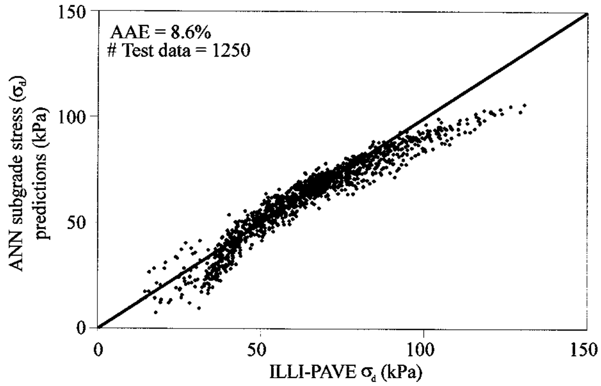

Fig. 1: Prediction of subgrade deviator stress, σ_d

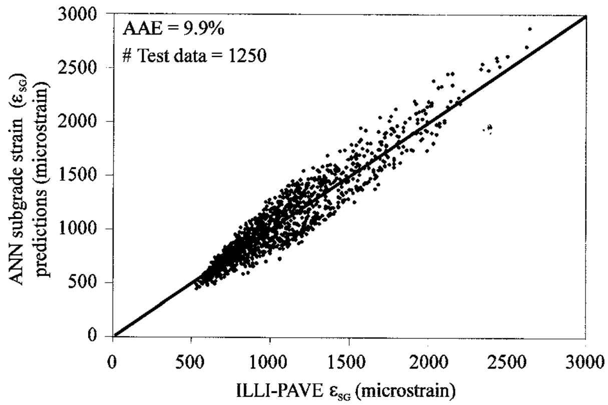

Fig. 2: Prediction of vertical subgrade compressive strain, ε_{SG}

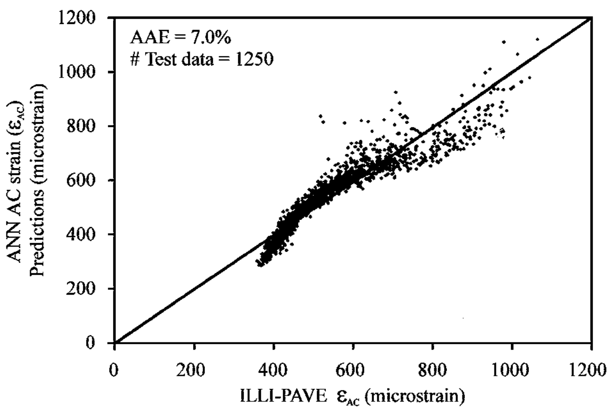

Fig. 3: Prediction of horizontal tensile AC strain, ε_{AC}

Using the results from ILLI-PAVE finite element analyses, researchers have showed that the SSR is a good indicator of the subgrade condition (Bejarano and Thompson, 1999). The philosophy of the SSR criterion is to ensure that the pavement exhibits stable subgrade permanent deformation performance. The SSR criterion has been successfully utilized in the development of ILLI-PAVE based flexible highway pavement design procedures for the Illinois Department of Transportation (Thompson and Elliot, 1985). The SSR-based subgrade criterion has been proposed for airport flexible pavement design (Bejarano and Thompson, 1999).

Table 3: Summary of best-performance ANN prediction models

Output	Inputs	Network architecture	Testing average Absolute Error (AAE)
σ_d	$D_0 \sim D_5$	6-40-40-1	8.6%
ε_{SG}	$D_0 \sim D_5$	6-20-20-1	9.9%
ε_{AC}	$D_0 \sim D_5$, AUPP, E_{AC}	8-10-1	7%

Using the synthetic deflection basins generated by ILLI-PAVE and the derived DBPs, ANN-based models for predicting ε_{AC}, ε_{SG} and σ_d was developed. Initial analyses showed that predicting these layer condition indicators were extremely difficult. Of the three, ε_{AC} was the most difficult to predict. Previous studies have shown that the AC layer moduli (E_{AC}) and non-linear subgrade moduli could be successfully predicted from synthetic/realistic HWD deflection basins using ANN-based models (Gopalakrishnan, 2004). Table 3 displays the summary of all the best-performance ANN-based prediction models identified by the parametric analyses in this study. Note that the ANN model for predicting ε_{AC} includes the ANN-predicted AC modulus (E_{AC}) as an input together with the deflection measurements. The details of the training process and the parametric analysis conducted to identify the best-performance ANN models are reported elsewhere (Gopalakrishnan, 2004).

In Fig. 1 to 3, the target and ANN-predicted values are compared for all the output variables using the 1,250 test data vectors. Good agreement is found between the target and ANN-predicted values for all output variables with Average Absolute Errors (AAEs) ranging from 7 to 10%. Note that the AAEs were calculated as sum of the individual absolute errors divided by the 1,250 independent testing vectors. Further research is required to achieve increased prediction accuracies for these ANN-based models.

One of the major reasons driving this research is to develop methodologies for reliably evaluating the structural integrity of the NAPTF pavement test sections as they were subjected to repeated aircraft traffic loading. 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 Boeing 777 traffic lane, Boeing 747 traffic lane and the untrafficked Centerline (C/L). Future studies will focus on applying the ANN structural models developed in this study for predicting the critical pavement responses from the NAPTF HWD deflection basins.

DISCUSSION

In this study, ANN-based prediction models were developed to estimate the critical pavement structural responses using the ILLI-PAVE generated synthetic database. Unlike the conventional elastic layer pavement analysis programs which assume pavement geomaterials to be linear elastic, stress-sensitive stiffness models were used in ILLI-PAVE to account for the hardening behavior of unbound granular materials and softening behavior of fine-grained subgrade soils. In this study, ILLI-PAVE generated synthetic database was used to train and test ANN-based structural models developed for rapid and realistic structural analysis of airport flexible pavements.

The developed ANN-models predicted the critical pavement responses from the ILLI-PAVE synthetic finite-element database with reasonable accuracy. The Average Absolute Errors (AAEs) ranged from 7 to 10%. Further research is required to achieve increased prediction accuracies. The future work will focus on applying the developed ANN-based models for predicting critical pavement responses from actual non-destructive pavement evaluation test data collected at the National Airport Pavement Test Facility (NAPTF).

A significant benefit of using such validated ANN-based models in routine pavement analysis and design is that they provide the same sophistication as time-consuming finite element modeling (e.g., ILLI-PAVE) required for realistic characterization of pavement layers, but at the same time provide almost instantaneous results. As a result, they lend themselves easily to routine airfield pavement evaluation which require analyzing a large number of pavement deflection basins in real-time.

Future studies would incorporate a wide range of pavement layer properties in the training dataset which would improve the generalization capabilities of the ANN. Studies 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 critical pavement responses.

ACKNOWLEDGMENTS

This research was prepared from a study conducted in the Center of Excellence (COE) for Airport Technology. Funding for the COE is provided in part by the Federal Aviation Administration (FAA). The COE is maintained at the University of Illinois at Urbana-Champaign who works in partnership with Northwestern University and the FAA. Ms. Patricia Watts is the FAA Program Manager for Air Transportation COE and Dr. Satish Agrawal is the Manager of the FAA Airport Technology R and D Branch. The contents of this paper reflect the views of the authors who are responsible for the facts and accuracy of the data presented within. The contents do not necessarily reflect the official views and policies of the FAA. This research does not constitute a standard, specification, or regulation. The author gratefully acknowledges the financial assistance and support by Professor Marshall R. Thompson for conducting this research. The author is also grateful to Dr. Franco Gomez-Ramirez for his valuable help and suggestions in developing the training database. Special thanks to Dr. David R. Brill and Dr. Gordon Hayhoe of FAA and Dr. Navneet Garg of SRA International Inc. for their help in conducting this study.

REFERENCES

Bejarano, M. and M.R. Thompson, 1999. Subgrade soil evaluation for the design of airport flexible pavements. Final Report, COE Report No. 8, Department of Civil Engineering, University of Illinois at Urbana-Champaign, Urbana, Illinois.

Ceylan, H., E. Tutumluer, M.R. Thompson and F. Gomez-Ramirez, 2004. Neural network-based structural models for rapid analysis of flexible pavements with unbound aggregate layers. Proceeding of 6th International Symposium on Pavements Unbound (UNBAR6), Nottingham, England, UK.

Gopalakrishnan, K., 2004. Performance analysis of airport flexible pavement subjected to new generation aircraft. Ph.D. Thesis, University of Illinois at Urbana-Champaign, Urbana, IL.

Haykin, S., 1994. Neural Networks: A Comprehensive Foundation. Macmillan College Publishing Company, Inc., New York.

Hicks, R.G., 1970. Factors influencing the resilient properties of granular materials. Ph.D. Thesis, University of California, Berkeley.

Hicks, R.G. and C.L. Monismith, 1971. Factors Influencing the Resilient Properties of Granular Materials, Transportation Research Record 345, TRB, National Research Council, Washington, DC.

Hossain, S.M. and J.P. Zaniewski, 1991. Characterization of falling weight deflectometer deflection basin. Transportation Research Record 1293, TRB, National Research Council, Washington, DC.

Raad, L. and J.L. Figueroa, 1980. Load response of transportation support systems. ASCE J. Transportation Engineering, 16 (TE1).

Rada, G. and M.W. Witczak, 1981. Comprehensive evaluation of laboratory resilient moduli results for granular material. Transportation Research Record 810, TRB, National Research Council, Washington, DC.

Thompson, M.R. and Q.L. Robnett, 1979. Resilient properties of subgrade soils. ASCE. J. Transportation Eng., Vol. 105.

Thompson, M.R. and R.P. Elliot, 1985. ILLI-PAVE based response algorithms for design of conventional flexible pavements. Transportation Research Record 1043, TRB, National Research Council, Washington, DC.

Thompson, M.R. and D. Nauman, 1993. Rutting rate analysis of the AASHO road test flexible pavements. Transportation Research Record 1384, TRB, National Research Council, Washington, DC.

Xu, B., S.R. Ranjithan and R.Y. Kim, 2001. Development of relationships between FWD deflections and asphalt pavement layer condition indicators. Proceeding of 81st Annual Meeting of the Transportation Research Board, Washington, DC.