2015-01-01

A Rapid Approach For Considering Nonlinear Response Of Flexible Pavements Under Fwd And Estimation Of Remaining Lives Of Pavements

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Dedication

I would like to dedicate this thesis to my beloved family.

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by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Department of Civil Engineering

THE UNIVERSITY OF TEXAS AT EL PASO

December 2015

Acknowledgements

I would like to express my gratitude to my thesis advisor, Dr. Soheil Nazarian for his excellent guidance, caring, patience, providing me with an outstanding environment for me to do my research and giving me the opportunity to work as a graduate research assistant at the Center for Transportation Infrastructure Systems (CTIS). Without his excellent supervision and knowledge I would have never been able to complete this thesis. I would also like to state my gratitude to the Center's staffs, especially to Dr. Cesar Tirado and Imad Abdallah for giving me the opportunity to work along their sides. I will not forget the support of Dr. Tirado for his exceptional guidance these two years.

I would also like to thank my thesis committee members, Dr. Reza S. Ashtiani and Dr. Eric MacDonald for kindly accepting to be in my committee and for the time they took to review my thesis.

Finally, I would like to thank my wife, Maryam Esmaeilkhanian and my brother, Hamid Shirazi. They have always been there encouraging and standing by me through the good and bad times.

Abstract

Most mechanistic empirical pavement analyses are based on the layered elastic models where the stress sensitivity of geomaterials and their nonlinearity are either ignored or accounted for indirectly. Advanced numerical models, such as finite element models, are required to consider the nonlinear nature of the geomaterials. Existing pavements are often tested with the Falling Weight Deflectometer (FWD) to estimate the input moduli to the layered elastic models in order to estimate remaining life and structural capacity of pavements. It has been more than 30 years that FWD tests are being performed to measure structural adequacy of pavements. Backcalculation is the method of evaluation of pavement surface deflections caused by specific pavement deflection devices in order to determine the moduli of pavement layers. Even though the deflection bowls may be influenced by the load-induced nonlinearity during the FWD testing, the extraction of the layer moduli is carried out using a layered elastic forward model. For being consistent in evaluation of the readings, efforts to conduct backcalculation using the nonlinear algorithms are of great academic interest. Because of time consuming characteristic of nonlinear algorithm, this method is not practical for day-to-day implementation.

This thesis puts forward a methodology used to relate deflections obtained from nonlinear analysis to those of linear elastic under FWD loading condition at conventional locations. This thesis has two significant contributions. Firstly, the conversion of linear elastic deflections to nonlinear deflections enables one to take full advantage of fast layered elastic analysis of pavements while the geomaterials' stress dependency behavior is accounted for. Secondly, it will be shown in the relevant section that backcalculation based on linear elastic deflections at conventional locations results in a more realistic computation of layer moduli rather than simply using nonlinear field deflections.

In addition, the estimation of critical pavement responses using structural parameters of pavements and FWD readings is also discussed. The conventional approach to determine remaining lives of pavements consists of the following steps. FWD is applied on the pavement to

backcalculate layer moduli. Then the pavement becomes subject to design vehicle to calculate critical pavement strains using linear elastic software programs. Critical responses are then converted to allowable number of load application to reach failure. FWD loading is applied on various pavements while nonlinear material properties are present and deflections at conventional locations are measured using finite element (FE) analysis. FWD nonlinear field representative deflection bowls are simulated in the program. Then, equivalent single axle load (ESAL) dual tire is applied to the same pavement structures under linear elastic assumptions to follow the conventional procedure. Critical pavement responses include tensile strains at the bottom of HMA and compressive strains on the top of subgrade, are determined. ANNs are then developed to estimate these responses based on FWD readings and structural properties of the system. Backcalculation process oftentimes provides nonunique layer moduli. The usage of developed ANN provides the elimination of backcalculation process to estimate remaining life. Hence, by using ANN models one can predict remaining lives of pavements while there will be no need to go through backcalculation.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction and Background

1.1 Introduction

The conventional FWD backcalculation procedures are based on the linear elastic layered analysis where the pavement layers are assumed as homogeneous, isotropic and linear elastic, and the FWD loads are assumed to be applied in a static manner. However, the pavement layers may not act according to these ideal assumptions during field testing (Hadi and Bodhinayake 2003).

During the past decades, researchers have been trying to implement the finite element (FE) models to estimate the pavement responses more realistically at the expense of more time consuming analyses. The FE method enables one to select an appropriate constitutive model for each pavement layer separately.

Nonlinear resilient modulus of granular materials depends not only on the stress state applied to them, but their inherent characteristics specified by constant k values. Understanding the complex interactions among different nonlinear k material modulus parameters, as will be discussed in the relevant section extensively, and layer thicknesses and their relationships to the response parameters used in the evaluation of pavements are usually unknown or hard to identify. Soft computing techniques have been gaining popularity during the past decades to identify the complex relationship between the pavement known and response parameters. The artificial neural networks (ANNs) are valuable statistical learning models and powerful tools for estimating the approximate solutions to the complex nonlinear problems while setting relationship between the inputs and outputs. The ANN architecture involves a series of independent variables known as input neurons linked to a number of intermediate parameters (hidden neurons). The outputs are first estimated using seed random weights by the program. The error defined as the difference between the first calculated output and the target will then be back-propagated to the network to

adjust the initial weights (Hecht-Nielsen 1989). Because of their convenience, ANNs have been used in a lot of engineering fields.

Chapter one explains what the problem set to solve is. Chapter two discusses underlying concepts behind ANNs which is the statistical tool used in this study.

Chapter three encompasses developing ANN models that provide the ratio of the nonlinear to linear elastic deflections for different FWD sensors and for different pavement structures. The results from the ANN models can be multiplied by the deflections measured with the FWD device to estimate the linear-elastic deflection bowls for potentially a more rigorous backcalculation.

Chapter four provides a practical approach to ignore backcalculation procedure to estimate remaining lives of pavements using ANNs. It is shown that the generated ANNs are able to predict the critical responses of pavements given the FWD deflection basins and structural parameters of pavements without having to backcalculate layer moduli.

1.2 Problem Statement

1.2.1 Analysis

Because of the speed and convenience associated with them, mechanistic pavement analyses are mostly based upon linear elastic assumptions. There are various programs that calculate stresses, strains and deflection under these simplifying assumptions. Bisar (De Jong et al. 1973), CHEVRON (Michelow 1963) , WESLEA developed by the U.S. Army Corps of Engineers (Freeman and Harr 2004) are examples of such programs. However, because of the simplifying assumptions that this type of analysis makes, pavement responses calculated may not be realistic (Hadi and Bodhinayake 2003). On the other hand, FE analysis is believed to provide pavement responses that can be considered to be representatives of what actually happens in the

field (Hadi and Bodhinayake 2003). FE analysis, however, tends to be time consuming and is not practical to use on a regular basis.

One of the main aspects of this thesis was placed on finding a correlation based approach to adjust responses obtained from the linear elastic to those of nonlinear under FWD loading condition and at conventional geophone locations located at every 12 inches from the load. Therefore, one can still enjoy the speed associated with the linear elastic analysis while computation time is minimized.

1.2.2 Backcalculation

The falling weight deflectometer is a nondestructive test (NDT) being used for more than thirty years and has become a standard method of NDT for evaluation of roads. The purpose of FWD is to evaluate structural properties of pavements. Figure 1 shows the deflections measured by seven sensors under dynamic loading and in the presence of actual pavement materials.

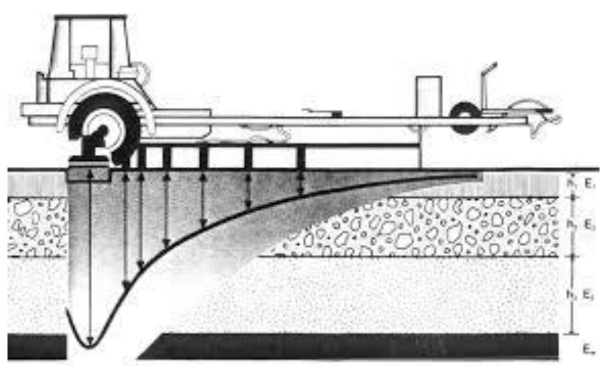

Figure 1 Deflection Bowls under FWD

Backcalculation is the most commonly used method for understanding structural capacity and soundness of the pavements from the FWD seven sensor deflection data (Rahim and George 2003). Conventionally, these seven surface deflections are computed by mechanistic analysis using the assumed moduli and layer thicknesses under linear elastic assumptions. The next level is to compare the calculated deflection to those obtained from field measurements. If the field

measured deflections and the ones obtained from linear elastic analysis match, the initial moduli selected are assumed to be correct. If not, then the seed moduli will change to adjust field deflections and the calculated ones. The iterative process continues until calculated and measure are within a predefined tolerance.

As explained, part of the backcalculation procedure consists of calculating deflections measured at different distances from the loading area with a mechanistic analysis method. Two methods are most frequently used for the backcalculation algorithm: Multi-layered elastic theory (Burmister 1945) and finite element method.

The issue is even though the deflections measured in the field may be influenced by material nonlinearity and the dynamic loading, backcalculated layer moduli are ‘’mostly’’ extracted from the software programs that work under linear elastic assumptions. Since nonlinear finite element backcalculation of pavements are not practical for day-to-day implementation because of their time consuming characteristic, a practical approach is suggested in this thesis to adjust responses obtained from the nonlinear analysis to those of the linear elastic for a potentially more rigorous backcalculation. As such, deflections measured in the field can be transferred to linear elastic ones and be input to linear elastic backcalculation software programs to backcalculate layer moduli. In a relevant chapter it will be discussed that backcalculation based on linear elastic deflection bowls results in a more reliable backcalculated layer moduli.

For that purpose, the ratio of the deflections from the nonlinear analysis to the deflection at the same location from the linear elastic analysis is termed as the “transfer value.”

1.3 ANALYSIS OF PAVEMENTS

1.3.1 Multilayered Elastic Theory

Burmister was the first one who introduced the simplest layered analysis of pavements. (Burmister et al. 1944). All mechanistic linear elastic analysis of pavements makes some simplifying assumptions. The following assumptions are the basics of these types of evaluations:

- Pavement materials are not loaded beyond their elastic range such that stress strain curve is a linear line.
- The subgrade layer continues infinitely downward.
- Pavement layers develop horizontally.
- Pavement layers are homogeneous and isotropic.
- Dynamic effects of the load is assumed to be negligible.

There are plenty of computer programs that allow for linear elastic analysis of pavements based on Burmister's layered elastic theory. These program allow the computation of stresses, strains and displacements at certain points within the system. ELSYM5, developed at the University of Kentucky (Kopperman et al. 1986), CHEV developed by Chervon Research company (Warren and Dieckmann 1963), BISAR developed by De Jong et al. (1973) that computes pavement responses under normal and tangential loads are all examples of software packages that handles structures with linear elastic layers.

Layered elastic models require the lowest number of inputs. Thickness of the layers, elastic modulus of pavement layers and Poisson's ratio are the essential inputs to these programs.

1.3.2 Finite Element method

Finite Element Method is a useful numerical technique that handles a wide variety of engineering problem with complex constitutive material models. It is also a valuable tool for

introducing complicated geometries into the program. It was originally developed to determine stresses in airframe structures. It has nowadays been further developed to the continuum mechanic field (Huebner et al. 2001). In the continuum mechanic problems (one that possess continuous mass or volume) the variable we are looking for may take wide range of values as it may be function of where it is located in the continuum. The stresses of a specific element in a continuum problem cannot be computed simply with an equation since stresses are not only dependent on material properties but on the location of the element. The same concept applies to pavement geomaterials' behavior as its fundamental resilient modulus behavior is highly location dependent (Puppala 2007). Because FE analysis takes into account resilient modulus locational dependency behavior, it has become a popular method to study pavement responses.

In this thesis, Intpave computer program developed by Tirado et al. (2007) was selected for the linear elastic and nonlinear FE analyses.

1.4 Literature Review

As discussed, finite element methodology provides more realistic results than simple linear elastic does (Hadi and Bodhinayake 2003). This approach evaluates pavement responses more realistically. Many researchers have studied different pavements under wide conditions after the development of general FE programs (e.g. ABAQUS, ADINA and ANSYS). Instances are (Sukumaran et al. 2004 and Schwartz 2002). Another example is a study done by Hadi and Bodhinayake (2003) proved that by using finite element method, the displacements under loading when nonlinear material properties are considered match best to deflections measured in the real field. Saad et al. (2005) studied the dynamic fatigue strain at the bottom of the asphalt concrete (AC) layer and the rutting strain at the top of the subgrade with a 3-D FE model under a single wheel load. Tirado et al. (2014) used the FE models to adjust the flexible pavement responses

gained from the linear elastic analysis to those from the nonlinear analysis. Zaghloul and White (1993) used a 3D dynamic finite element program called ABAQUS to study three layer flexible pavement responses under moving loads with varying speeds and different material models. Helwany et al. (1998) indicated the advantage of the finite element method in the analysis of three-layer pavement systems subject to different types of loading. Pavement responses such as maximum vertical displacement, radial strain at the bottom of AC layer, vertical strain on the top of subgrade layer under linear and nonlinear assumptions were then compared. They concluded if finite element modeling of pavements is validated, it could be used directly to obtain primary responses of pavements without having to perform costly field experiments for three layer pavements. Further, they showed that primary responses required in damage prediction could be analytically measured with FE analysis for varying types of axles with different loading speeds.

ANNs are also being considered as a powerful statistical tool to link a series of inputs to one or more outputs. A study by Abdallah et al. (2000) proved the ease with which ANN can be used to predict remaining lives of flexible pavements due to rutting and fatigue cracking using FWD deflection basins and structural properties of the pavement. Shirazi et al. (2009) developed ANN to replace the backcalculation process for the spectral analysis of surface wave (SASW) method used for nondestructive testing (NDT) of pavements. Abo-Hashema (2013) discusses the feasibility of applying ANN in predicting the HMA layer temperature using the air temperature as input. Shafabakhsh et al. (2014) used ANNs for predicting the longitudinal strains at the bottom of the hot mix asphalt (HMA) layer in flexible pavements subjected to moving wheel loads.

Chapter 2: ANN Basics and Feedforward Backpropagation Neural Networks

2.1 BACKGROUND

Artificial neural networks (ANNs) are statistical learning method inspired by human brains which has been used successfully in so many fields to solve pattern recognition problems (Panakkat and Adeli 2009). The idea that relates ANNs to actual human biological neural network is the fact that in the brain, neurons are connected to each other through pathways that pass on information from one neuron to another (Jain and Fanelli 2000). Figure 2 shows diagram of a biological neuron versus an artificial neuron (Shirazi 2005). In ANN each neuron can be considered as a processing unit that has inputs and outputs. When one neuron receives a response from a cell, after processing it redirects the output to the other neurons that it is connected to. (Basheer and Hajmeer 2000).

Since complex networks consist of individual neurons, hereafter it will be shown how an individual neuron works. Then the algorithm of multilayer neural network used in this thesis will be discussed in the next section. Figure 3 demonstrates how an individual cell takes inputs through connections, processes them through a function, and sends the response out.

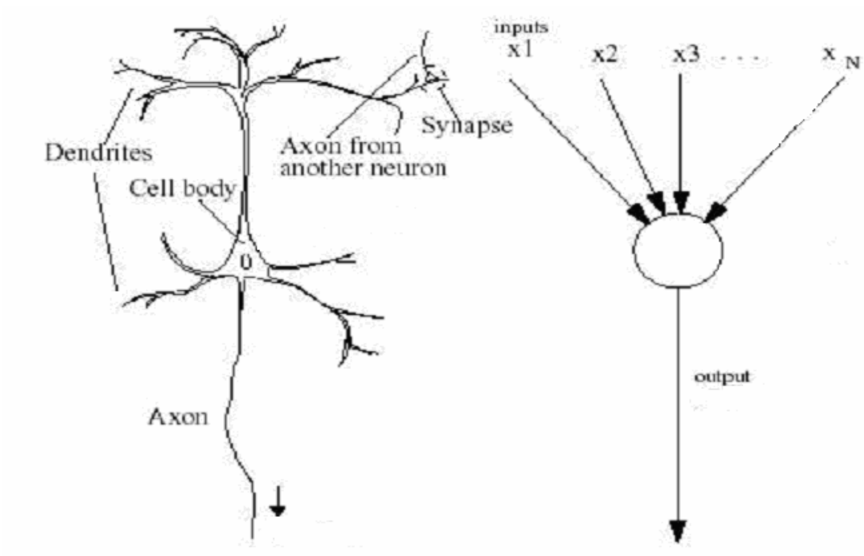

Figure 2 Biological Neuron vs. Artificial Neuron

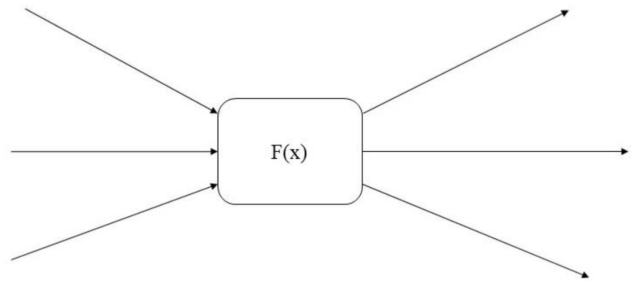

Figure 3 Functioning of an Individual Cell in a Network

Each neuron either takes inputs from other neurons, output layer or hidden layers, or takes them from independent values, input layer. The impact of all inputs to the desired output is not the same within a network. The difference in the level of importance of each input is addressed through its connection weights. The higher the weights of an input is, the higher would be its effect on the desired output value. To adjust the weights connected to a neuron, firstly the neuron calculates the weighted sum of inputs (Zin) and then applies an activation function on it (f) to generate output. The output of this neuron will be the input to neuron of the next layer in the overall view of the network (Rumelhart et al. 1985). Figure 4shows a schematic of a neuron in a network (Shirazi 2005). The mathematical form of showing the activation function and weighted sum of inputs are:

$$Z_{in} = \sum_{i=1}^{n} xiwi \qquad \textit{Equation1}$$

$$Z = f\,(z_{in}) \qquad \textit{Equation 2}$$

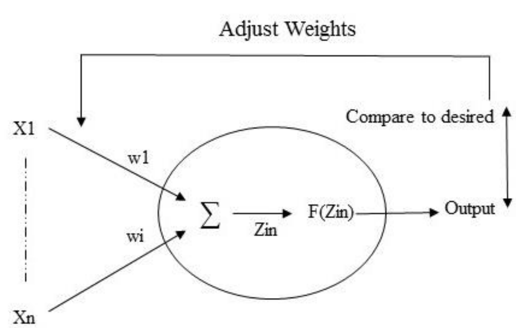

Figure 4 Diagram of a Neuron in a Network

As shown in Figure 4, in the training process of a neuron, initial random weights are first set up. Then the output computed from these weights is compared with the desired target value. If the difference exceeds a predefined value, the weights are adjusted until the output is nearly equal to the desired value. Once this specified criterion is met, the neuron has been trained and weights are final.

2.2 MULTILAYER FEEDFORWARD BACKPROPAGATION NEURAL NETWORKS

Neural networks (NN) are divided in different ways based on their tasks (Specht 1967), architecture (Hassoun 1995) or learning method they use (Yao 1999). According to architecture point of view, neural networks are divided into three main categories. Feedforward NN, recurrent NN and cellular NN (Shirazi et al. 2009). Multilayer feedforward backpropagation NN are the most commonly used networks. There are three layers in a network. Input layer, hidden layer and output layer. In the feedforward networks, except for backpropagation discussed later, the neuron connection weights are in only one direction. What it implies is that neurons of a layer are not linked to the neurons of the same layer but connected to that of the next layer. Figure 5 is a schematic of a feedforward NN consisting of input layer, hidden layer and output layer.

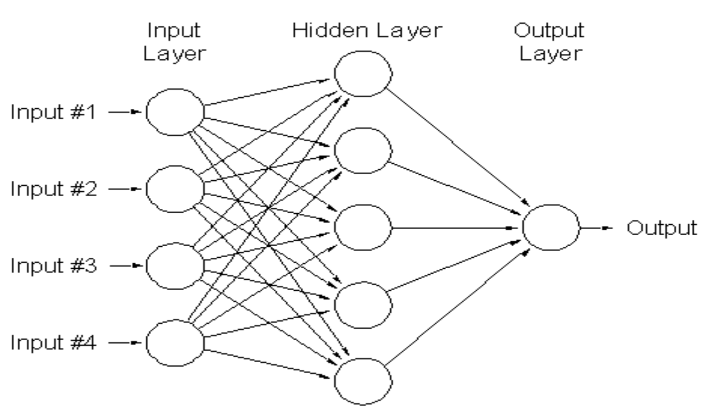

Figure 5 Feed-forward Neural Network

The network has n, p and m neurons in input, hidden and output layer, respectively (n-p-m network). There is another element that each layer has with a value of one. This element is called bias. The learning method with which this NN works is called backpropagation. The backpropagation training algorithm tries to minimize the error function which is the difference between desired value and the output. Therefore, the combination of weights with which the error function is minimized will be the solution to the learning problem.

The training algorithm has three levels (Graupe 2007). The first stage includes assigning initial weights to all the connections throughout the network and moving from the inputs towards hidden and consequently the output layer through the weighted connections. Obviously the output cannot even be expected to be even close to the desired output and the error will be relatively large.

Within the second level, the difference between the output and target is back propagated from the output layer to the input layer to adjust for the primary assigned connection weights. It can be simply proved that the weights with stronger connections are more responsible for the error. In this stage the share of each weight in making the error will be calculated.

In the third stage, weights are adjusted in a way that new connections aim to minimize the desired value. Each time this process is operated within computer is called one epoch. This iterative process continues until one of the stopping criteria is met. The network now has been trained and the weights computed in the last epoch will then be used for projection of future sets of inputs.

The built-in Matlab feed-forward ANN routine was used as the training function for the estimation of the transfer values. The number of hidden layers were changed to select the one with best statistical result. About 70% of the database (7000 cases) were considered for training, 15% for validation and the other 15% for testing.

Chapter 3: Data Collection and Methodology

3.1 DATA COLLECTION

A total of 10,000 random combinations of input data were generated to develop three-layered pavement systems for the finite element analysis. The hot mix asphalt (HMA) and base thicknesses were varied from 1 in. to 12 in. and 6 in. to 18 in., respectively in 0.1 in. increment to cover all feasible ranges of thickness. The HMA modulus was varied from 300 ksi to 700 ksi. Poisson's ratio of the layers were considered as 0.35, 0.3 and 0.4 for AC, base and subgrade layer respectively. Velasquez et al. (2009) suggested the feasible range over which the nonlinear k parameters in Equation 3 for the base and subgrade materials might vary. For coarse and fine-grained materials, they suggested the numbers provided in Table 1.

Table 1 Feasible Range of k Parameters of Granular Materials

k parameters	Course grained materials	Fine grained materials
k_1	400 - 3000	1000 - 4000
k_2	0.2 - 1	0.01 - 0.5
k_3	-0.9 - -0.1	-6.0 - -1.5

In order to generate a pavement database for the FE simulation, Latin hyperbolic sampling (LHS) was used to construct a sample size of 10,000 pavement structures. In this level, the range and distribution of each key pavement properties (e.g. thicknesses and nonlinear k parameters) explained earlier were used. The LHS was first proposed by McKay (1992) used for generating sample of plausible collections of parameter values. LHS sampling method is a tool usually used to artificially generate input dataset whose variables are evenly distributed over the defined range(Liu 2013). Built-in Matlab function called "lhsu" was used for that purpose. This function takes sample size, minimum and maximum of all variables and returns an n by p vector with n and

p being sample size number and number of variables, respectively. The developed database was saved for finite element analysis.

3.2 Finite Element Analysis

The FE software package called the Integrated Pavement Damage Analyzer (Intpave) developed at The University of Texas at El Paso handles the flexible pavement structures with either the nonlinear or linear elastic material properties (Tirado et al. 2007). That program takes advantage of an optimized mesh in which the elements become diminutive when close to the load application area and larger farther from the load where the load-induced stresses dissipate. This transition results in a less number of elements and saves the computation time. The generated mesh is a 3-D structure consisting of the four-node, tetrahedral elements whose geometric flexibility allow the intricate geometric modeling and facilitate the transition from the coarsely meshed zones to the finely meshed zones. Figure 6 displays how elements are expanded as they go farther from the loading area.

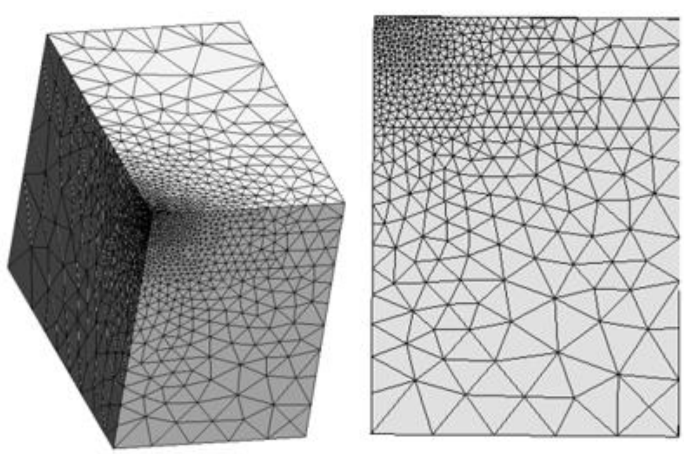

Figure 6 Three-Dimensional Mesh with Refined Elements in Intpave

For both linear and nonlinear analyses a 3-D model consisting of a 100 in. x 100 in. section of the pavement was modeled. A 9000-lb FWD loading was simulated as an 80 psi pressure directly applied to the nodes within a 6 in. radius. Similar to the FWD tests, the vertical deflections were registered at distances of 0, 12, 24, 36, 48, 60 and 72 in. away from the load. The subsequent subsection explains how pavement layers were modeled in the program.

3.2.1 Moduli of Pavement Layers

The resilient modulus (MR) tests are the most common laboratory tests used to characterize the unbound base, subbase, and subgrade materials for the mechanistic-empirical pavement design procedures. The most common material models used in pavement engineering are the global models that relate the modulus to the bulk and octahedral shear stresses as pioneered by Uzan (Puppala, 2007). In those models, the stress-dependent nonlinear behaviors of different unbound layers are characterized using:

$$M_R= k_1 P_a \left[\frac{\Theta}{Pa}\right]^{K2} \left[\frac{\tau oct}{Pa}+1\right]^{K3} \qquad \textit{Equation 3}$$

where P_a is the atmospheric pressure, θ is the bulk stress, τ_{oct} is the octahedral shear stress, and k_1, k_2, k_3 are regression coefficients determined from the resilient modulus laboratory testing. The mathematical form of determining bulk and octahedral shear stresses are the following:

$$\theta= \sigma_1 + \sigma_2 + \sigma_3 \qquad \textit{Equation 4}$$

$$\tau = 1/3\sqrt{(\sigma_1-\sigma_2)^2+(\sigma_1-\sigma_3)^2+(\sigma_2-\sigma_3)^2} \qquad \textit{Equation5}$$

Considering Equation 3, the moduli needed for the design are affected by the state of stress imposed by the vehicular loads. Since the state of stress is a function of the selected layer moduli, the only way to select a self-consistent representative modulus for each layer has to be through an iterative process (Tirado et al., 2014). Iterative process consists of the following three stages. In

step one approximate layer moduli are assumed for granular layers based on engineering judgment. Then in stage two the load is applied and stress state for all elements in the program is calculated. Stage three includes entering the computed stresses into the equation 3 to check if the resilient modulus calculated falls within predefined acceptable range compared to assumed value. If the calculated modulus is close enough to the assumed value, then assumed modulus and computed stresses and strains are accepted. If the difference is more than a predefined tolerance, the next iteration is carried out to adjust the moduli of all elements. This process continues until one of the stopping criteria is met.

To avoid this iterative process for practicality, representative states of stress for base (τ_{oct}= 7.5 psi and Θ = 31 psi) and subgrade (τ_{oct}= 3 and Θ = 12.4 psi) proposed by NCHRP 1-28A were used (Tirado et al. 2014). As discussed in Tirado et al. (2014), these assumptions may be reasonable in the vicinity of the applied wheel load; however, they may not be representative of the modulus of the material farther from the load (i.e., the outer sensors of the FWD). In this study, these recommended stresses were used as the initial values for the iterative process which were updated in the subsequent iterations. In both analyses HMA layer was simulated as ordinary linear elastic. The next two sections provides essential information about modeling pavement structures under nonlinear and linear elastic assumptions. Representative stresses recommended by NCHRP 1-28 were considered for finding resilient modulus of granular layers in linear elastic analysis.

3.3 Linear Elastic versus Nonlinear Deflections at Seven Locations

Figure 7 contains a typical comparison of the linear elastic and nonlinear deflection bowls along the surface of a thin pavement section. For almost all pavements considered (thick or thin),

the linear elastic and the nonlinear surface deflections close to the loading area varied to various degrees. In contrast, they compared well with one another farther from the loaded area.

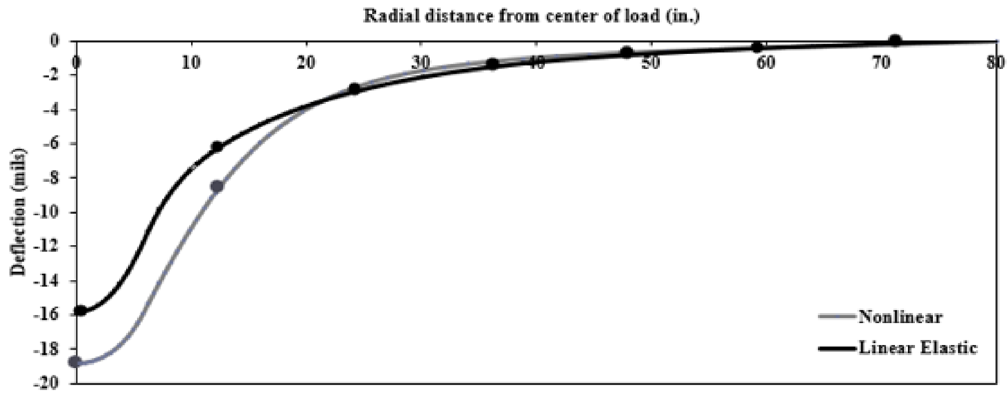

Figure 7 Comparison of Typical Linear and Nonlinear Deflection Bowls

The first interpretation that can be made from the Figure 7 is that deflections computed using linear elastic analysis is not necessarily equal to the ones computed from nonlinear analysis. Remaining life of pavements is typically evaluated by providing the backcalculation programs with the nonlinear FWD field seven deflections to backcalculate layer moduli. Figure 7 is important because it makes a huge difference whether a user input linear elastic deflections to a backcalculation program or nonlinear ones. Evidently, which deflection bowls type is used will directly affect the corresponding estimation of remaining life of the road. In section 3.4.1 four different pavements will be backcalculated using both nonlinear and linear deflection bowls. It will be also discussed that backcalculation using linear elastic deflection bowls leads to a more promising backcalculated layer moduli by comparing them to the representative resilient moduli suggested by NCHRP 1-28.

The other fact that can be seen from the Figure 7 is that sensors close to the loading area seem to be more affected by material nonlinearity simply because the difference between the two

linear elastic and nonlinear deflections decrease as we move along the surface. It can be stated that the last two sensors are marginally affected by geomaterial nonlinear behavior. For comparison purposes between the two responses, combination of a series of statistical criteria must be considered at the same time to justify the fact that sensors are less and less affected by geomaterials' nonlinear behavior along the surface. Slope of the trend line which passes through the two deflection bowls types, R^2 and standard error of estimate (SEE) will be considered hereafter.

Table 2 compares all of these three statistical criteria at the seven sensor locations. In addition to these statistical standards, magnitude of both deflection types and difference between them are other important factors for us to consider. As an example statistical criteria for deflection at 0 is discussed and compared with the rest of the geophone locations.

A trend line was forced to pass through origin to see what the slope of the line would be. The slope of the line for deflections at zero is 1.34. It shows that for most of the cases nonlinear deflection tends to be greater than linear elastic one. According to

Table 2 this value decreases and becomes inclined to 1 from 0 to 72 that is the desired value. Even though the slope of the line drops down to 0.75 at 72 in. from the load, SEE and R^2 are good enough to consider this sensor as ''neutral sensor'' to material nonlinearity. SEE is a measure of scatter of two variables around the regression line. As shown in

Table 2, SEE goes down consistently as we move from 0 to 72 which contributes to the idea that material nonlinearity's impact decreases in a consistent way. On the other hand, since the stresses are dissipated at locations farther away from the load, the magnitude and difference between the two responses are considerably low. All things considered, the last two geophones can be considered as the ones that are marginally affected by geomaterial nonlinear behavior.

Therefore, for the last two sensors, simple linear regression lines in Table 3. Figure 9 shows the result of nonlinear versus linear elastic deflections at 60 and 72 inches from the load are suggested to estimate the linear elastic response based on nonlinear and vice versa. Simple linear regression fits a line through two sets of variables in such a way that the line makes the sum of squared error minimal (Chatterjee and Hadi 2006).

Table 2 Material nonlinearity impact on all sensors

Sensor location	Slope	SEE	R^2
0	1.34	3.03	0.91
12	1.37	2.28	0.72
24	1.22	1.23	0.64
36	1.1	0.82	0.71
48	1.03	0.55	0.79
60	0.97	0.37	0.84
72	0.75	0.25	0.89

Table 3 Simple Linear Regression Model for the Last Two Sensors

Last two sensors (in.)	Simple Linear Regression
60	Nonlinear = 0.901*Linear Elastic + 0.1292
72	Nonlinear = 0.892*Linear Elastic +0.0647

From what stated above and shown in Table 2 it is concluded that the deflections of sensors at 0, 12, 24, 36 and 48 in. from the load are more affected by the nonlinear behavior of the base and subgrade. Figure 8 shows the results of nonlinear deflections at these locations versus linear elastic ones. Traditional regression models often times have serious shortcomings and fail to identify complex relationships among various parameters Ter Braak (1986). Hence, for a more satisfactory model development, for the five sensors up to 48 inches ANN models were considered to correlate the two responses.

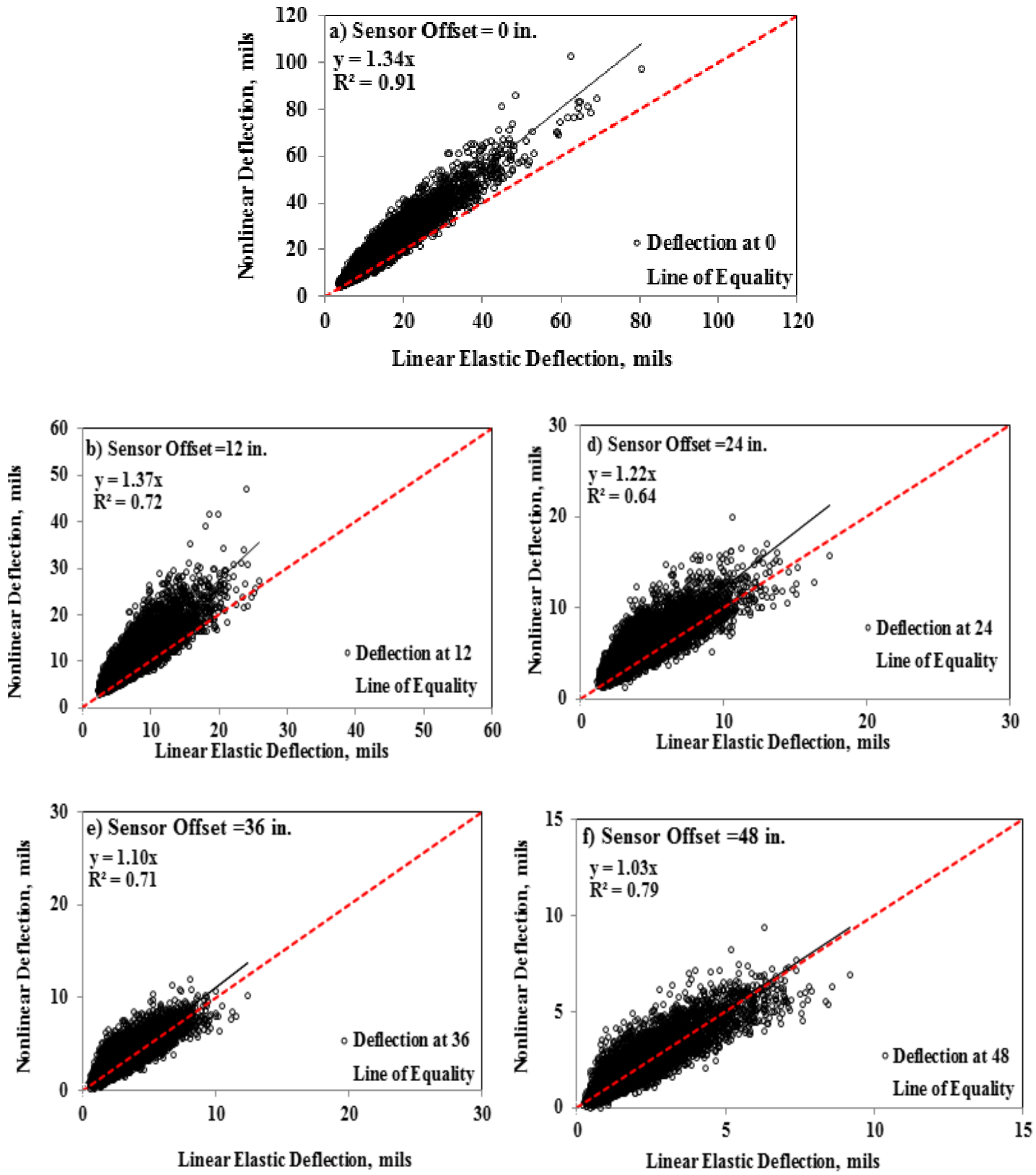

Figure 8 Sensors Affected by Nonlinear Material Properties of Granular Layers

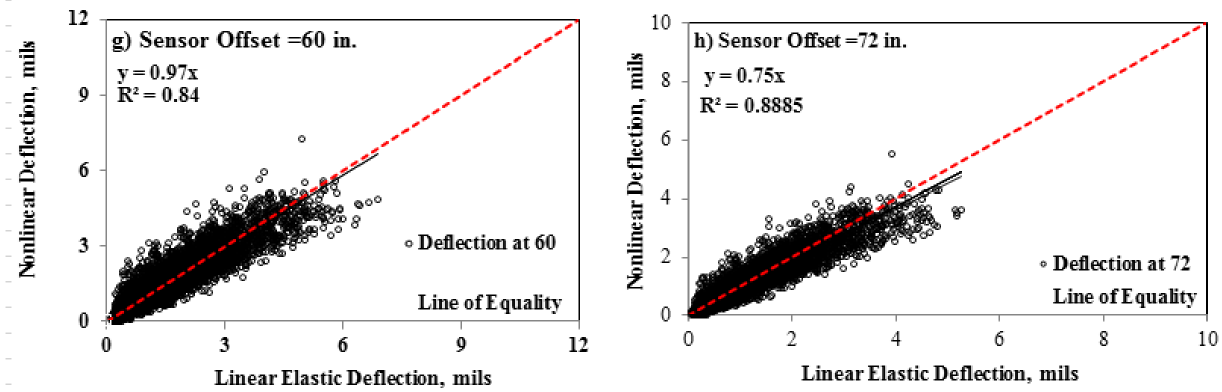

Figure 9 Sensors marginally affected by Nonlinear Material Properties of Granular Layers

3.4 Transfer Values Projections with Artificial Neural Network (ANN)

Neural network models were considered to relate the responses from the linear elastic and nonlinear analyses. The thickness of the HMA and base layer, modulus of HMA, the nonlinear constitutive model parameters k_1, k_2 and k_3 of base and k_1, k_2 and k_3 of subgrade were considered as potential parameters for input layer of the ANN. Correlation analyses were carried out first to minimize the number of structural parameters and nonlinear material parameters needed for training the ANNs.

Table 4 shows the correlation values between the transfer values at conventional locations and ANN potential inputs. The parameters that exhibited negligible impact on the transfer values were excluded from the evaluation to minimize the complexity associated with the implementation of ANN models. The correlation analyses showed that the input parameters affecting the transfer values are different for different sensors. The parameters that had correlation value of less than 0.1 were considered as the parameters that their presence in the input layer of ANN either had no influence on the performance of the model or worsen the statistical criteria associated to the model.

Therefore, they were excluded from the ANN inputs. As such, a separate ANN model had to be trained for each FWD sensor.

In addition, thicknesses of base and HMA, hardening k_2 parameter of base layer and nonlinear k_1, k_2 and k_3 of subgrade layer were the factors that marginally or strongly contribute to the transfer value to vary. Among these parameters, nonlinear material properties k_2 and k_3 of subgrade as well as hardening k_2 parameter of the base layer showed high impact on the degree of nonlinearity. According to Table 5, these values were commonly used as inputs of the ANN models. Table 5 summarizes the model parameters used for the input layers of different ANN models developed in this thesis.

Table 4 Correlation Values between Transfer Values at Different Locations and Structural Properties

Sensor Location (in.)	Thickness (in.)		HMA Modulus	k_1 base	k_2 base	k_3 base	k_1 Subg	k_2 Subg	k_3 Subg
	HMA	Base							
0	-0.32	0.27	-0.03	0.00	0.72	0.05	0.06	0.37	0.21
12	-0.30	0.28	-0.04	-0.08	0.66	0.06	0.13	0.41	0.28
24	0.11	0.26	0.00	-0.24	0.50	0.09	0.15	0.49	0.37
36	0.31	0.17	0.04	-0.29	0.32	0.08	0.11	0.49	0.37
48	0.39	0.1	0.06	-0.28	0.20	0.02	0.07	0.50	0.36

Table 5 Model Parameters Used for Each Sensor Offset

Sensor Location, (in.)	Input Parameter								
	Thickness (in.)		Base Material Parameters			Subgrade Material Parameters			HMA Modulus
	HMA	Base	k_1	k_2	k_3	k_1	k_2	k_3	
0	√	√		√			√	√	
12	√	√		√		√	√	√	
24	√	√	√	√	√	√	√	√	
36	√	√	√	√	√	√	√	√	
48	√	√	√	√		√	√	√	

The models were evaluated using three different criteria; namely R2 or coefficient of determination, standard error of estimate (SEE) and slope of the line between the observed FE transfer values and the transfer values predicted from the ANN model. Goodness of the fit is defined as the extent to which a statistical model can fit to a set of observations. Goodness of the fit is usually explained by the coefficient of determination (R^2) and the SEE. Then, estimated transfer values are compared with the observed FE values to see how well the developed ANN is. When R^2 is 0 it indicates that the model does not address variability of the target around the mean. In contrast, if it is 1 it shows that predicted values match to observation data. Also, a standard error of 0 means that the model has no random error. The bigger the SEE is the less accurate would be the model. As shown later in the result section of this chapter, the predicted ANN transfer values are in agreement with the observed FE values.

3.4.1 Improvement in Backcalculation of Pavements Using Linear Elastic Deflections

One of the most important applications of the FWD measurements is to determine the remaining lives of pavements through the use of the backcalculated layer moduli. While most of the backcalculation software programs work under the linear elastic assumptions, the deflection bowls measured in the field may be influenced by the material nonlinearity. The developed ANNs are capable of transferring the nonlinear deflection bowls measured in the field to equivalent linear elastic ones at the seven sensor locations for potentially more precise backcalculation outcomes. To demonstrate how different the backcalculated moduli based on the linear and nonlinear deflection bowls could be, four typical pavement sections consisting of different HMA and base thicknesses were considered. The software package ‘’MODULUS’’ (Jooste et al. 1998) was used for the backcalculation purposes.

Table 5 displays the pavement sections that were used for this purpose. (Oh and Fernando 2011) suggested that the stress states suggested by the NCHRP 1-28 to be a good approximation of the field condition. Backcalculated layer moduli with the linear elastic and nonlinear deflection basins are compared in Table 6 with representative moduli recommended by NCHRP 1-28. The backcalculated layer moduli based on the linear elastic deflection basins are closer to the representative resilient moduli suggested by NCHRP 1-28. Developed ANNs are capable of transferring the nonlinear deflection bowls measured in the field to those of linear elastic for a potentially more precise backcalculation.

Table 5 Pavement Structures Used for Comparing Backcalculated Layer Moduli Based on Linear Elastic and Nonlinear Deflections

Case Number	Input Parameter								
	Thicknesses (in.)		Base Material Parameters			Subgrade Material property			HMA Modulus (psi)
	HMA	Base	k_1	k_2	k_3	k_1	k_2	k_3	
1	5.5	9.8	1977	0.66	-0.88	1217	0.11	-5.05	387000
2	4	12.2	1527	0.26	-0.89	1742	0.13	-4.89	443000
3	5	7.3	2601	0.87	-0.39	2105	0.38	-2.79	424000
4	6	9.3	2941	0.76	-0.71	2935	0.19	-2.1	325000

Table 6 Backcalculated Layer Moduli Based on Seven Linear Elastic and Nonlinear Deflections Compared to Representative MR

Case Number	Analysis Type	Backcalculated Moduli, ksi			Representative MR	
		HMA	Base	Subgrade	Base	Subgrade
1	Nonlinear	493	10	11	33	6
	Linear	527	32	9		
2	Nonlinear	595	13	16	18	10
	Linear	545	19	13		
3	Nonlinear	669	10	22	62	17
	Linear	654	56	26		
4	Nonlinear	340	45	30	57	28
	Linear	461	55	38		

3.4.2 ANN models Results

Figure 10 shows the comparison of the predicted transfer values from the ANN models with the calculated transfer values from the linear and nonlinear FE analyses for sensors located between 0 and 48 in. from the load. The R^2 values of the relationships between the observed FE transfer values and the predicted ANN ones are in excess of 0.9, indicating high certainty in using the ANN for analysis and backcalculation procedure at all locations. Also, SEE which is a measure of how scattered two sets of variables are, is less than 0.05 at 0, less than 0.07 at 12 in., less than 0.1 at 24 in., less than 0.08 at 36 and less than 0.1 at 48 showing developed ANN results are in accordance with what was actually expected according to FE results. In addition, slopes of the trend line which passes through the origin tends to be very close to 1 supporting the margin of error to be minimal.

As stated earlier, because the linear and nonlinear deflections for the two geophones at 60 and 72 inches from the load compare well to one another, simple linear regression was considered for them instead of developing ANN.

Using the developed ANN, one can take full advantage of more sophisticated nonlinear FEA deflection while the computation time is minimized.

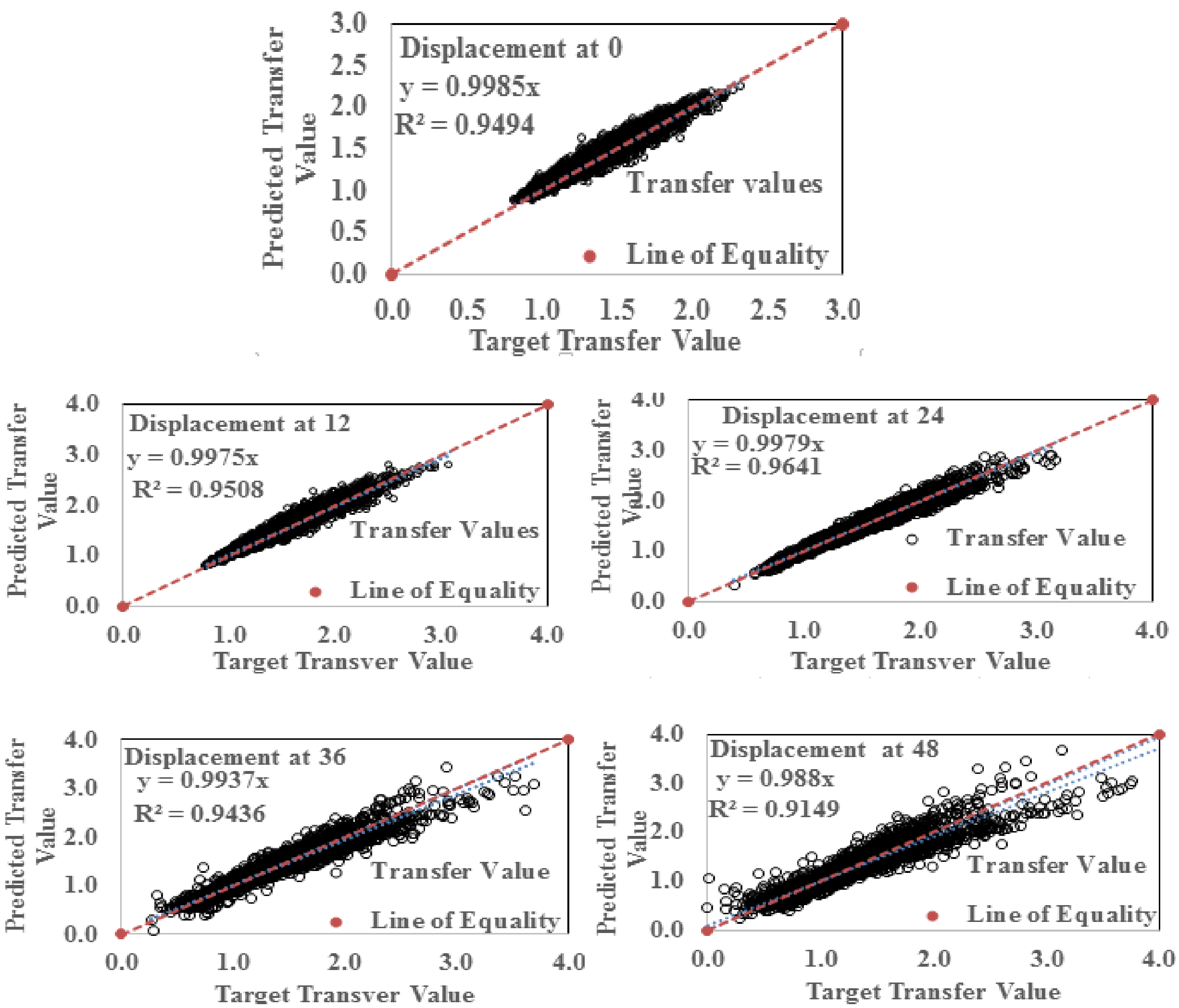

Figure 10 Prediction of Transfer Functions for FWD Displacements at all Sensor Offsets

Chapter 4: Estimation of Remaining Lives of Pavements Using FWD Field Deflection Bowls

Fatigue and rutting failure mechanisms are the two most important distresses by which pavement structures may fail. Fatigue failure is attributed to the tensile strain of asphalt layer while rutting is believed to initiate due to compressive strain on top of subgrade layer. The tensile strain at the bottom of HMA and compressive strain on the top of subgrade have been identified as good performance indicators (Huang 1993). For evaluation purposes, the tensile strain of asphalt layer and the compressive strain on top of subgrade are calculated using elastic layered programs where the pavement is subject to the design vehicle. Results are then transferred to various types of distresses using transfer functions to predict remaining lives of pavements.

Critical strains caused by the design vehicle are usually used to estimate remaining lives due to fatigue and rutting (Huang 1993). Rutting models have the following general form:

$N_r = f_1\, (\varepsilon_c)^{-f_2}$ Equation 6

And, fatigue cracking models take the following general form:

$N_f = f_3\, (\varepsilon_t) - f_4\, (EAC) - f_5$ Equation 7

Where N_r is the ultimate number of equivalent single axle loads (ESAL) applications that the pavement can tolerate before failure, and N_f is the ultimate number of load applications that pavement can sustain before failure, f1 to f5 are constant coefficients.

The overall procedure to evaluate the remaining lives of pavement is basically through employing FWD deflections to backcalculate layer moduli and then extraction of critical strains under a design vehicle. This method may lead to deficient evaluation as the backcalculated moduli are sometimes nonunique. (Yu 2005) This chapter aims at developing ANN models that are capable of estimating the critical pavement responses under a design vehicle. Potential inputs to the ANNs are the FWD nonlinear FE deflections and the pavement structural parameters.

4.1 LINEAR ELASTIC ESAL DUAL TIRE ANALYSIS AND CRITICAL STRAINS

Intpave program discussed earlier is capable of investigating different loading scenarios. The same 3-D model used for FWD analysis was utilized in Intpave to simulate the responses of the pavements under 18000 lb. equivalent single axle load (ESAL) Tires were assumed to be rectangular with length and width of 8 in. and 6 in., respectively, with 12 inches tire spacing, Figure 11. The same database developed for the FWD simulations was executed under the linear elastic assumptions to obtain the critical pavement responses. Poisson's ratios of the layers were considered as 0.35, 0.3 and 0.4 for AC, base and subgrade layer respectively.

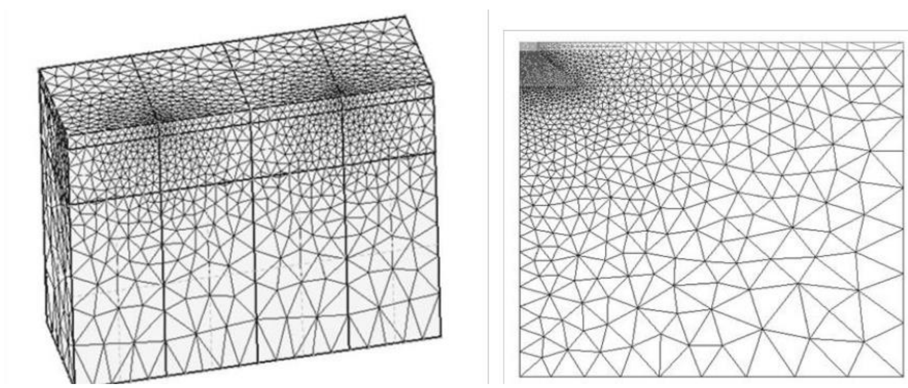

Figure 11 Three Dimensional Mesh with Refined Elements under ESAL Dual Tire in Intpave

The locations of the critical pavement responses depend on loading configuration and structural profile of the pavement system (Terrel et al. 1974). The location of critical values for the pavement structure under single and dual wheel loading are shown in Figure 12 and Figure 13. Under single loading, the critical values happen directly beneath the tire. However, for the cases with dual tires the maximum controlling critical strains occur either directly under the load or midway between them (Terrel et al. 1974). Because the highest critical strains are used to estimate the progressions of the alligator cracking and permanent deformation, ideally the maximum strains have to be estimated. Tensile strains along the x, longitudinal, and z directions, transverse, at the bottom of HMA for both scenarios shown below in the Figure 13, were retrieved from the FE

program. The maximum tensile strain among the four values, tensile strain in the direction of the moving truck under the load and midway between tires and tensile strains perpendicular to the direction of moving truck under the load and midway between tires, was selected.

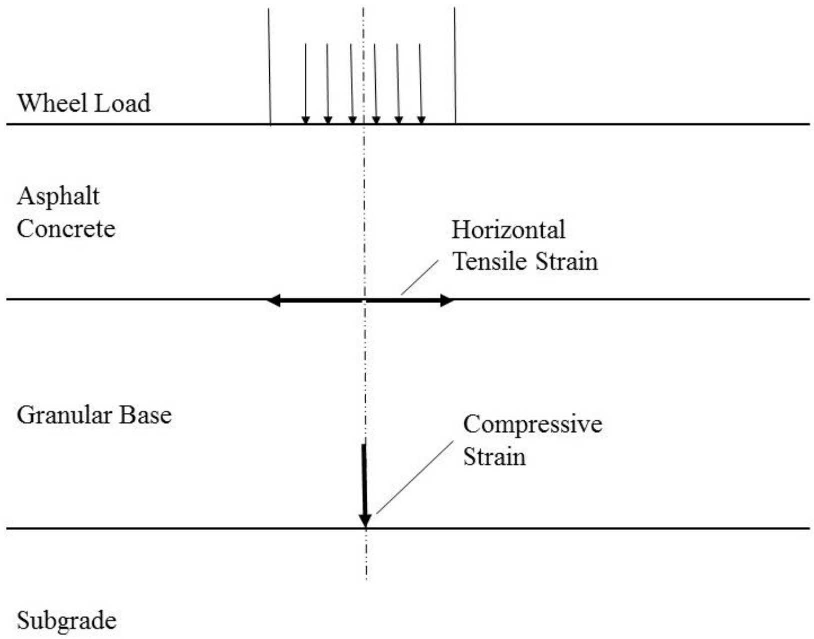

Figure 12 Location of Critical Pavement Responses under Single Tire

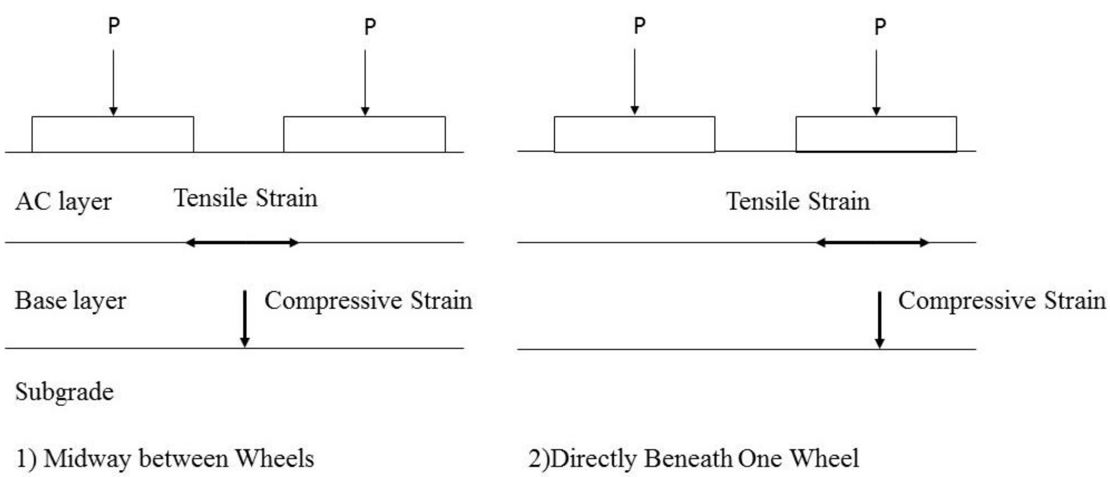

Figure 13 Location of Critical Pavement Responses under Dual Tire

4.2 Critical Response Projection Using ANN

The built-in Matlab feed-forward ANN routine was used as the training function for the estimation of the critical pavement responses. The number of hidden layers were changed to select the one with best statistical result. About 70% of the database (7000 cases) were considered for training, 15% for validation and the other 15% for testing.

4.2.1 Maximum Tensile Strain Projection Using ANN

Neural network models were considered to relate the FWD synthetic deflection bowls and the structural parameters of the flexible pavements to the maximum tensile strain at the bottom of the HMA layer. The thickness of the HMA and base layers, the material model parameters k_1, k_2 and k_3 of the base and subgrade were considered as potential input parameters to the ANNs.

Table 7 contains the results of a correlation analysis between the input parameters and the maximum tensile strains. Those variables that had correlation of less than 0.1 with the target either had no effect on the generated ANN model or, even in some cases, aggravated its performance. As expected, fatigue performance of the structures has a very high correlation with thickness and modulus of the asphalt layer which is a relatively intuitive fact. Also, it can be interpreted that the higher the softening parameters of the base layer is the less would be the tensile strain imposed on the bottom of the HMA layer. In addition, material properties of subgrade layer almost have nothing to do with fatigue performance of the pavements.

Table 7 Correlation between Maximum Tensile Strain at the Bottom of HMA, Structural Properties of Pavements and Nonlinear FWD Deflection Basins

Input Parameter	*t-HMA*	*t-base*	*E-HMA*	*k1-base*	*k2-base*	*k3-base*	*k1-subg*	*k2-subg*	*k3-subg*	*0*	*12*	*24*	*36*	*48*	*60*	*72*
Correlation Coefficient	-0.25	-0.05	-0.13	-0.46	-0.14	-0.10	0.00	-0.02	-0.02	0.53	0.30	0.04	-0.03	-0.02	-0.01	0.01

Table 8 demonstrates what inputs to the ANN model for prediction of maximum tensile strain are. Figure 14 displays the result of the best-generated ANN for the maximum tensile strain.

Table 8 Max Tensile Strain Model Parameters Used for Development of ANN

Input Parameter	Thickness (in.)		Base Material Parameters			Subgrade Material Parameters			FWD Deflections at Sensor Locations (in.)							HMA Modulus (psi)
	HMA	Base	k_1	k_2	k_3	k_1	k_2	k_3	0	12	24	36	48	60	72	
Significance	√		√	√					√	√						√

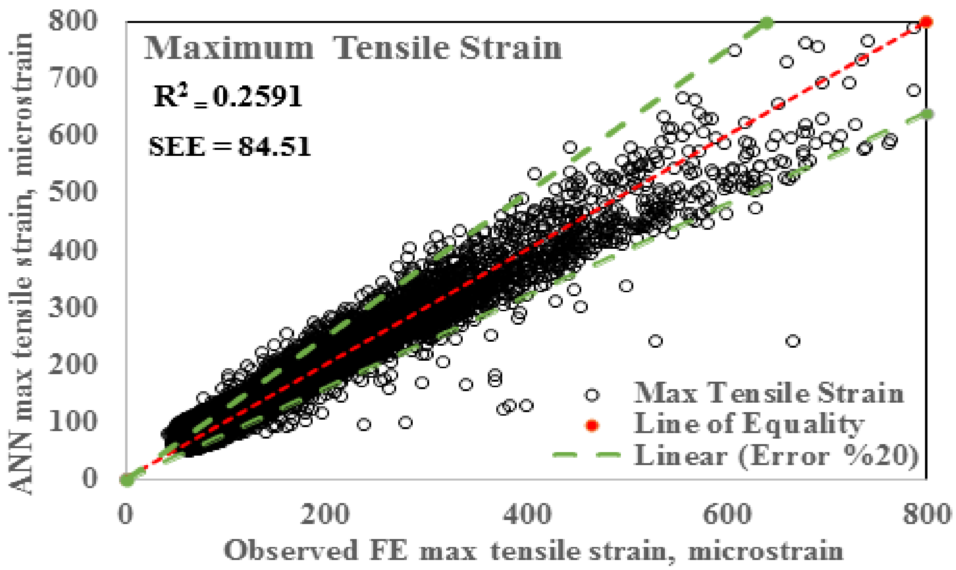

Figure 14 Estimation of Max Tensile Strain under Dual Tire Loading

To improve the model certainty, it was assumed that the maximum tensile strains will always happen at the midway between the two tires. As such, the maximum strains were chosen as the largest of the longitudinal and transverse tensile strains at midway between the tires. Table 9 shows correlation coefficients between different structural parameters and the maximum tensile strain midway between wheels. As shown in Figure 15, the R^2 value improved from 0.259 to 0.96 and also the SEE from 84.51 to 14.72 micro strain. However, this improved performance of the model comes with the location of the critical strain.

Table 9 Correlation between Maximum Tensile Strain between Tires at the Bottom of HMA with Structural Properties of Pavements and Nonlinear FWD Deflection Basins

Max Tensile Strain between tires	*t-HMA*	*t-base*	*E-HMA*	*k1-base*	*k2-base*	*k3-base*	*k1-subg*	*k2-subg*	*k3-subg*	*0*	*12*	*24*	*36*	*48*	*60*	*72*
	-0.58	-0.04	-0.19	-0.48	-0.16	-0.09	-0.05	0.00	-0.04	0.73	0.66	0.23	-0.04	-0.13	-0.16	-0.15

Table 10 Max Tensile Strain Model Parameters Used for Development of ANN

Input Parameters	Input Parameter															
	Thickness (in.)		Base Material Parameters			Subgrade Material Parameters			FWD Deflections at Sensor Locations (in.)							HMA
	HMA	Base	k_1	k_2	k_3	k_1	k_2	k_3	0	12	24	36	48	60	72	E
Significance	√		√	√					√	√	√					√

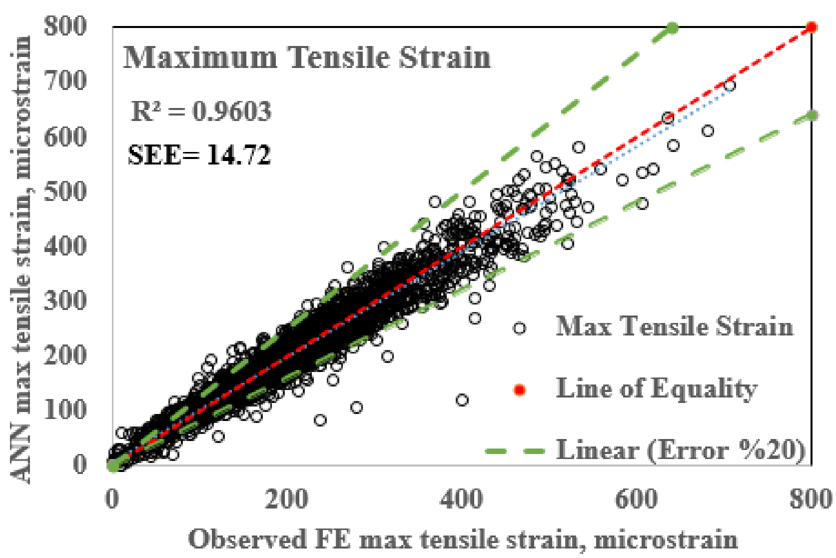

Figure 15 Estimation of Maximum Tensile Strain at Midway between Tires

4.2.2 Maximum Compressive Strain Projection Using ANN

The same procedure used for the critical tensile strain was considered for the maximum compressive strain. The conventional sign for the compression is negative in FE. However,

since in pavement positive sign stands for compression, absolute values were used to model compressive strain on top of subgrade. Two compressive strains (midway between the tires and beneath one of the tires) on top of subgrade were compared and the one with the highest absolute value was assumed to be the critical parameter for estimating rutting. Table 11 demonstrates the correlation coefficients for different input parameters. As discussed earlier, the structural parameters and FWD deflections that had no effect on the maximum compressive strain created on the top of subgrade were excluded from the ANN input layer. To that end, the parameters that had correlation of less than 0.1 were not considered for training the ANN model. According to Table 11, obviously, the thicker the upper layers are, the lower would be the stresses and strains that are being applied to the subgrade. This point can be figured out by looking at -0.69 and -0.31 correlation coefficients between maximum compressive strain and asphalt and base layer, respectively. Asphalt layer thickness seems to be more than twice as significant as base layer in mitigating vertical compressive strains. The magnitudes of FWD first three deflection bowls can be considered as good indicators of rutting performance of the whole pavement system. Table 12 contains the parameters that had correlation coefficients of greater than 0.1 that were selected for the ANN input layer. Given that the material properties of the subgrade play an important role in the rutting performance of the entire system, it was expected that the critical compressive strain will show high dependency on the nonlinear parameters of the subgrade. As expected, the maximum vertical compressive strain had a reasonably high dependency on the nonlinear material parameter k_1 and k_3 of the subgrade.

Table 11 Correlation between Maximum Compressive Strain, Structural Parameters of Pavements and FWD Deflection Basins

	t-HMA	*t-base*	*E-HMA*	*k1-base*	*k2-base*	*k3-base*	*k1-subg*	*k2-subg*	*k3-subg*	*0*	*12*	*24*	*36*	*48*	*60*	*72*
Max Compressive Strain between Tires	-0.69	-0.31	-0.08	-0.06	-0.03	-0.01	-0.36	0.05	-0.24	0.80	0.71	0.31	0.09	0.02	0.01	0.01

Table 12 Maximum Compressive Strain Model Parameters Used for Development of ANN

Input Parameter	Input Parameter															
	Thickness (in.)		Base Material Parameters			Subgrade Material Parameters			FWD Deflections at (in.)							HMA (psi)
	HMA	Base	k_1	k_2	k_3	k_1	k_2	k_3	0	12	24	36	48	60	72	E
Significance	√	√				√		√	√	√	√	√				

Figure 16 shows how well the generated ANN model predicted the compressive strains. According to the statistical results, there seems to be a high accuracy with the developed model as the predicted compressive strains are in agreement to the observations coming out of FE analysis.

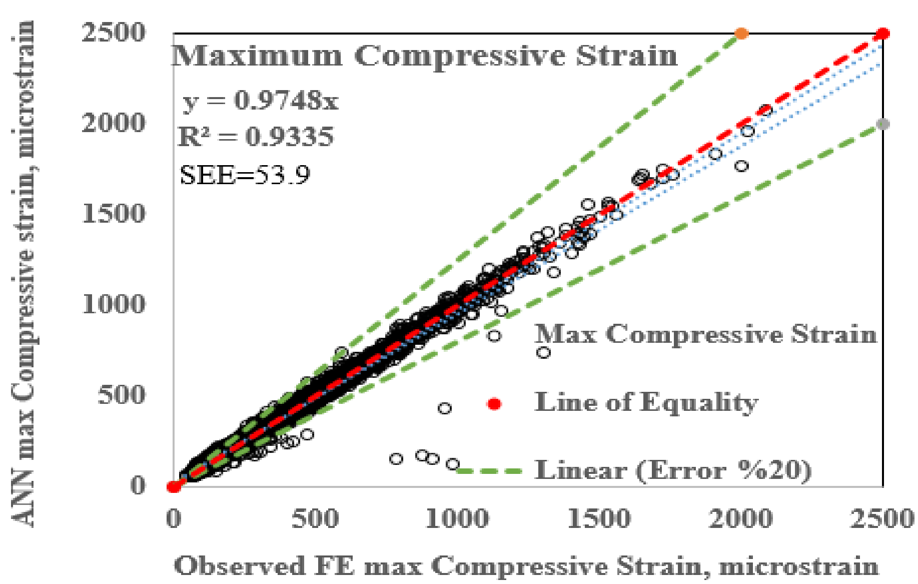

Figure 16 Estimation of Maximum Compressive Strain under Dual Tire Loading

Chapter 5: Conclusions

The first two chapters of this thesis explain the necessary background of this thesis. The third chapter appraised the differences between the deflections assessed from the nonlinear analysis and the linear elastic analysis. A finite element software package called Integrated Pavement Damage Analyzer (Intpave) was used for this purpose. The following conclusions can be drawn from the evaluation.

- Nonlinear deflections derived from FEA were substantially different from the linear elastic analyses for sensor deflections up to 24 inches, and they agreed better as the sensor spacing increased farther.
- Since the changes in the stress state is not addressed in the linear elastic analyses, a practical approach is recommended to convert the linear elastic results to those that are more compatible with the nonlinear analyses.
- Presumed values of the octahedral and bulk stresses recommended by the NCHRP 1-28A is only an approximation for evaluation purposes. The use of the ANN models is recommended to take into account the effects of nonlinearity of the geomaterials.
- The ANN models trained as part of this study may be used to convert the measured FWD deflections from nonlinear analyses to equivalent linear elastic deflections for a more realistic backcalculations.

Chapter four of this thesis suggested a practical way to predict the critical pavement responses due to an ESAL from the FWD readings and structural properties of flexible pavement systems. The following can be interpreted from this section:

- The conventional procedure of using the backcalculated layer moduli to evaluate the remaining life of pavements may not be accurate as layer moduli may be nonunique.

- Using the developed ANN models provides a practical way to avoid the backcalculation process.

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Vita

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