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Computationally efficient surrogate response models for mechanistic-empirical pavement analysis and design

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Abstract
This paper proposes the use of neural network- (NN-) based pavement structural analysis tools as surrogates for the flexible pavement response analysis in the new mechanistic empirical pavement design guide (MEPDG) developed for the American State Highway and Transportation Officials (AASHTO). Some of the recent successful applications of NN-based structural analysis models for predicting critical flexible pavement responses and nonlinear pavement layer moduli from falling weight deflectometer (FWD) deflection basins are highlighted. Because NNs excel at mapping in higher-order spaces, such models can go beyond the existing univariate relationships between pavement structural responses and performance (such as the subgrade strain criteria for considering flexible pavement rutting). The NN-based rapid prediction models could easily be incorporated into the newer versions of the MEPDG, which will continue to be updated. This can lead to better performance prediction and also reduce the risk of premature pavement failure.

Keywords
backcalculation, flexible pavements, mechanistic-empirical pavement design guide, neural networks

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Computationally Efficient Surrogate Response Models for Mechanistic-Empirical Pavement Analysis and Design

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Abstract

The purpose of a pavement response model is to determine the structural response of the pavement system due to traffic loads and environmental influences. This paper proposes the use of Neural Network (NN) based pavement structural analysis tools as surrogates for the flexible pavement response analysis in the new Mechanistic Empirical Pavement Design Guide (MEPDG) developed for the American State Highway and Transportation Officials (AASHTO). Neural networks have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional numerical and statistical methods. Some of the recent successful applications of NN structural analysis models developed at Iowa State University for predicting critical flexible pavement responses and non-linear pavement layer moduli from Falling Weight Deflectometer (FWD) deflection basins are presented. Because NNs excel at mapping in higher-order spaces, such models can go beyond the existing univariate relationships between pavement structural responses and performance (such as the subgrade strain criteria for considering flexible pavement rutting). The NN based rapid prediction models could easily be incorporated into the newer versions of MEPDG which is currently being updated. This can lead to better performance prediction and also reduce the risk of premature pavement failure.

Keywords: Flexible pavements, neural networks, mechanistic-empirical pavement design guide, back calculation

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1. Introduction

The purpose of a pavement response model is to determine the structural response of the pavement system due to traffic loads and environmental influences. The Elastic Layered Programs (ELPs) used in flexible pavement analysis assume linear elasticity. Pavement geomaterials do not, however, follow a linear type stress-strain behavior under repeated traffic loading. In effect, nonlinear stress sensitive response of unbound aggregate materials and fine-grained subgrade soils has been well established (Brown and Pappin 1981, Thompson and Elliott 1985, Garg *et al.* 1998).

Unbound aggregates exhibit stress hardening or stiffening whereas fine-grained soils show stress softening type behavior. When these geomaterials are used as pavement layers, the layer stiffnesses, i.e., moduli are no longer constant but functions of the applied stress state. Pavement structural analysis programs that take into account nonlinear geomaterial characterization, such as the ILLI-PAVE finite element program (Raad and Figueroa 1980) need to be employed to more realistically predict pavement response needed for mechanistic based pavement design.

In the recent Mechanistic Empirical Pavement Design Guide (MEPDG) developed for the American Association of State Highway and Transportation Officials (AASHTO), two flexible pavement analysis methods have been implemented (NCHRP 2004). For cases in which all materials in the pavement structure can realistically be treated as linearly elastic, multilayer elastic theory is used to determine the pavement response. In cases where the unbound material nonlinearity is also considered, a nonlinear finite element procedure is used instead for determining the pavement stresses, strains, and displacements. However, the nonlinear finite element code provided with the guide is time-consuming and has not been validated or calibrated for routine design.

The recent adoption and use of Neural Networks (NN) modeling techniques in the recent MEPDG (NCHRP 2004) has especially placed the emphasis on the successful use of neural nets in geomechanical and pavement systems. Neural networks models developed using the ISLAB 2000 (Khazanovich *et al.* 2000) finite element structural model were employed in the MEPDG for providing rapid solutions of critical pavement responses for various combinations of input parameters. This paper proposes a similar approach for the rapid and accurate prediction of flexible pavement critical responses and backcalculation of flexible pavement layer moduli for use in MEPDG and in routine pavement analysis and design. NN models trained with the results from the ILLI-PAVE solutions have been found to be viable alternatives and could be used as surrogates for the flexible pavement response analysis in the MEPDG.

The Mechanistic-Empirical Pavement Design Guide

The AASHTO Guide for Design of Pavement Structures (AASHTO 1993) is currently used by most State highway agencies in the USA to design new and rehabilitated highway pavements. There are various editions of the AASHTO design guide (1972, 1986, and 1993), but they are all empirically based on performance equations developed using the 1950's AASHO Road Test (AASHO 1962) data. Although the various editions of the AASHTO design guide have served well for several decades, many have questioned their continued use for the analysis and design of new and rehabilitated pavements as material specifications, traffic volumes and weights, tire types and pressures have changed significantly since the time of 1950's AASHO Road Test (AASHO 1962).

In recognition of the limitations of the current AASHTO Guide, the AASHTO Joint Task Force on Pavements (JTFP) initiated an effort to develop an improved pavement design procedure based on Mechanistic-Empirical (M-E) concepts. The product of this effort is the newly released MEPDG based on the NCHRP Study 1-37A (NCHRP 2004).

The MEPDG relies on actual traffic operating at appropriate speeds and tire pressures and uses mathematical models to analyze the stress states within the pavement structures under appropriate local environmental conditions, which can change over the span of the design life of the pavement. The stress states at each time interval are used to evaluate and accumulate specific distress types using distress models calibrated with a comprehensive pavement performance database. Thus, the core of the mechanistic-based design model applied in the proposed MEPDG is the structural response models. Based on amongst others the traffic loads and climatic factors, the structural response models compute the resulting critical stresses, strains and displacements in flexible as well as rigid pavement systems. The computed responses are then applied to the damage models, which accumulate the incremental damages month by month over the entire design period.

The incremental design procedure adopted in the MEPDG requires hundreds of thousands of stress and deflection calculations to compute monthly damage (for the different loads, load positions, and equivalent temperature differences) over a design period of many years. These computations would take days to complete using existing finite element programs. To reduce computational time to a practical level, NN models have been developed for rigid pavement analysis, based on the ISLAB2000 Finite Element (FE) structural model (Khazanovich *et al.* 2000), to accurately compute critical stresses and deflections almost instantaneously. This makes it possible to conduct detailed, month-by-month, incremental analysis within a practical time frame (within a few minutes). A series of NN models were developed for different analyses that accurately reproduce the results given by direct FE analysis (R^2 of 0.99) and are presented in Appendix QQ of the MEPDG (NCHRP 2004).

For flexible pavement analysis, two methods have been implemented in the MEPDG. For cases in which all materials in the pavement structure can realistically be treated as linearly elastic, multilayer elastic theory is used to determine the pavement response. In cases where the unbound material nonlinearity is also considered, a nonlinear finite element procedure is used instead for determining the pavement stresses, strains, and displacements.

The selected structural response model applied for flexible pavements in the MEPDG is based on the multi-layer elastic program JULEA (linear elastic analysis) combined with the 2-D finite element program DSC2D (The DSC2D program is only applied when the user chooses to use the level 1 input to characterize the non-linear moduli response of any unbound layer materials (such as bases, sub-bases and/or sub-grades)). It should be noted that due to the complexity of these particular cases, calculation of this particular type is currently extremely time consuming and further development in this area will be required for future use.

This paper proposes the use of NN models trained with the results from the finite-element based ILLI-PAVE solutions as surrogates for the flexible pavement response analysis in the MEPDG. The use of such NN structural models not only accounts for the non-linear, stress-dependent behavior of pavement geomaterials, but also provides rapid solutions making the MEPDG analysis faster and accurate for routine design purposes.

2. Neural Networks as Pavement Analysis Tools

Neural networks are valuable computational tools that are increasingly being used to solve resource-intensive complex problems as an alternative to using more traditional techniques. Over the past two decades, there has been an increased interest in the use of NNs in civil engineering fields such as structural engineering, environmental and water resources engineering, traffic engineering, geotechnical engineering as well as pavement engineering. Neural networks offer a number of advantages, including the ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms.

NNs have been found to be useful tools for solving pavement engineering problems, which deal with highly nonlinear functional approximations. In the past, NNs have been used for predicting pavement performance and condition, selecting pavement management and maintenance strategies, pavement distress forecasting, structural evaluation of pavement systems, image analysis and classification, pavement material modeling, and for other miscellaneous pavement applications.

Imitating the biological nervous system, artificial neural networks are information processing computational tools capable of solving nonlinear relations in a specific problem (Adeli 2001). Like humans, they have the flexibility to learn from examples by means of interconnected elements, namely neurons. Neural network architectures, arranged in layers, involve synaptic connections amid neurons which receive signals and transmit them to the other via activation functions. Each connection has its own weight and learning is the process of adjusting the weight between neurons to minimize error between the predicted and expected values. Also, in the learning process node biases are also adjusted in addition to the connection weights. Since interconnected neurons have the flexibility to adjust the weights, neural networks have powerful capacities in analyzing complex problems (Adeli and Hung 1995).

Neural networks motivated by the neuronal architecture and operation of the brain contribute to our understanding of several complex, nonlinear pavement engineering problems with various pavement and soil variables. Fig. 1 displays a typical structure of NNs that consists of a number of neurons that are usually arranged in layers: an input layer, hidden layers, and output layers.

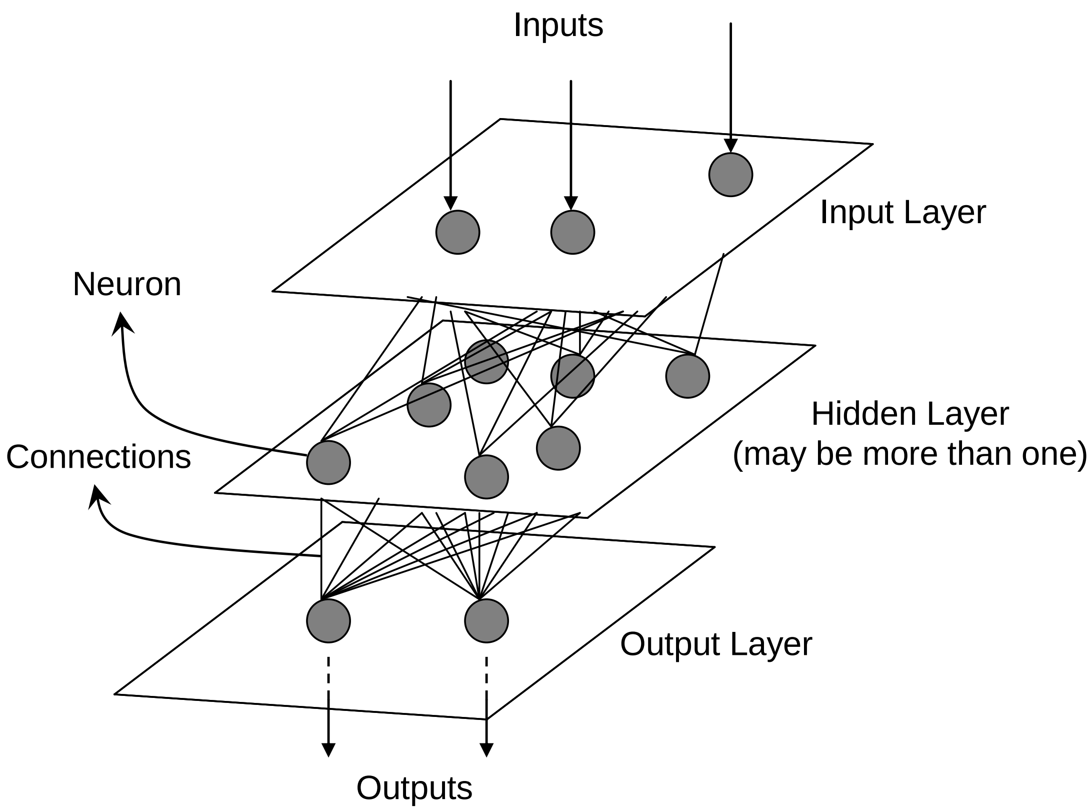

Fig. 1. A general schematic view of the NN architecture.

Neural network modeling has shown great promise as a useful and nontraditional computing tool for analyzing too complex, non-linear problems inherent to pavement engineering. NNs have the potential to investigate, properly model and, as a result, better understand some of the complex pavement engineering mechanisms that have not been well understood and formulated yet. This is especially possible with the vastly powerful and nonlinear interconnections provided in the network architecture that enables an NN to even model very sophisticated finite element method numerical solutions as the state-of-the-art pavement structural analysis results.

It should be acknowledged that despite their good performance in many situations, neural networks suffer from a number of shortcomings. For example, neural networks usually converge on some solution for any given training set. Unfortunately, there is no guarantee that this solution provides the best model of the data. Therefore, the test set must be utilized to determine when a model provides good enough performance to be used on unknown data. Also, a NN model has to come with supervised training, which basically gives a set of inputs and corresponding outputs. However, a NN model is specific to the scenarios where training samples are taken. Accuracy of the prediction with a NN model would not be guaranteed if the prediction goes beyond the scope of the scenarios, or say, if 'extrapolation' would have to be done. In many cases, the advantages of neural networks appear to outweigh these limitations.

There are different types of artificial neural network types such as Back-Propagation (BP) algorithms, Radial Basis Function (RBF) networks, Probabilistic

Neural Networks (PNN), and Generalized Regression Neural Networks (GRNN). The best-known example of a neural network training algorithm is back-propagation (Rumelhart *et al.* 1986, Haykin 1999, Fausett 1994, Patterson 1996) which is based on a gradient-descent optimization technique. The back-propagation algorithm is described in many textbooks (Adeli and Hung 1995, Haykin 1999, Hegazy *et al.* 1994, Mehrotra *et al.* 1997). The backpropagation NNs are very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of patterns/examples to be learned. The term "backpropagation network" actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. The learning process performed by this algorithm is called "backpropagation learning" which is mainly an "error minimization technique" (Haykin 1999). By far, this is the most commonly used NN in pavement engineering applications.

Meier *et al.* (1997) trained backpropagation type NNs as surrogates for ELP analysis in a computer program for backcalculating flexible pavement layer moduli and realized a 42 times increase in processing speed. Similar NN applications were also reported by Meier and Rix (1995), Gucunski and Krstic (1996), Khazanovich and Roesler (1997), and Kim and Kim (1998).

Ceylan (2002) mapped the solutions of nonlinear, stress-dependent finite element runs using NNs and compared the NN-based predictions of the pavement layer moduli with the results obtained from the backcalculation programs using linear elastic assumption of the pavement layers. In an earlier application at University of Illinois, Ceylan (2002) employed NNs in the analysis of concrete pavement systems and developed NN-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.

The capability of NN models to compute lateral and longitudinal tensile stresses as well as deflections at the bottom of jointed concrete airfield pavements as a function of type, level, and location of the applied gear load, slab thickness, slab modulus, subgrade support, pavement temperature gradient, and the load transfer efficiencies of the joints was illustrated by Ceylan *et al.* (1998, 1999 and 2000) and Ceylan (2002). The training sets were developed for prescribed gear and temperature loads using the ISLAB2000 finite element program. The findings of these studies proved that NN models could be successfully trained to capture the complex multi-dimensional mapping of a large-scale finite element pavement analysis problem in their connection weights and node biases. As mentioned previously, the NCHRP 1-37A research project team working on the development of the MEPDG for AASHTO have also recognized NNs as nontraditional, yet very powerful computing techniques and took advantage of NN models in preparing the concrete pavement analysis package (NCHRP 2004).

Recent research at the Iowa State University has focused on the development of NN based forward and backcalculation type flexible pavement analysis models to predict critical pavement responses and layer moduli, respectively (Ceylan *et al.* 2004; Ceylan *et al.* 2006; Gopalakrishnan *et al.* 2006).

In the field, pavement deflection profiles are obtained from FWD measurements, which require the use of backcalculation type structural analysis to determine pavement layer stiffnesses and as a result estimate pavement remaining life. The FWD test is one of the most widely used tests for assessing the structural integrity of roads in a nondestructive manner. Although NN modeling was used in the past to aid in backcalculation (Meier *et al.* 1997), the structural models used to train the NN models did not account for realistic stress sensitive geomaterial properties. For this reason, the ILLI-PAVE finite element program (Raad and Figueroa 1980), considering the nonlinear stress-dependent geomaterial characterization, was utilized to generate a solution database for developing NN-based structural models to accurately predict pavement critical responses and deflection basins from realistic FWD deflection profiles.

Such NN models could be implemented as surrogates for the flexible pavement response analysis in the MEPDG, thus enabling pavement engineers to easily and quickly incorporate the needed sophistication in structural analysis, such as from finite element modeling with proper characterization of pavement layers, into routine structural design.

3. Nonlinear Geomaterials Characterization

Considering increased serviceability and performance requirements of today's pavements, the field stress states, repeated application of moving traffic loads, field temperature and moisture are among the most important factors to be correctly accounted for in pavement structural analysis.

Under the repeated application of moving traffic loads, most of the pavement deformations are recoverable and thus considered elastic. It has been customary to use resilient modulus (M_R) for the elastic stiffness of the pavement materials defined as the repeatedly applied wheel load stress divided by the recoverable strain. Repeated load triaxial tests are commonly employed to evaluate the resilient properties of unbound aggregate materials and cohesive subgrade soils. Therefore, emphasis should be given in structural pavement analysis to realistic nonlinear material modeling in the base/subbase and subgrade layers primarily based on repeated load triaxial test results (AASHTO T307-99). The resilient moduli obtained at different applied stress states from the repeated load triaxial tests can best be characterized using nonlinear models expressing modulus as a function of applied stresses.

Simple resilient modulus models are often suitable for finite element programming and practical design use, such as:

K-θ Model (Hicks and Monismith 1971): $$M_R = K\left(\theta/p_o\right)^n \quad (1)$$

Universal Model (Uzan *et al.* 1992): $$M_R = K_1\left(\theta/p_o\right)^{K_2}\left(\tau_{oct}/p_o\right)^{K_3} \quad (2)$$

where $\theta = \sigma_1 + \sigma_2 + \sigma_3 = \sigma_1 + 2\sigma_3$ = bulk stress, τ_{oct} = octahedral shear stress = $\sqrt{2}/3 \times \sigma_d$ (where $\sigma_d = \sigma_1 - \sigma_3$ = deviator stress in triaxial conditions), p_0 is the unit reference pressure (1 kPa or 1 psi) used in the models to make the stresses non-dimensional, and K, n, and K_1 to K_3 are multiple regression constants obtained from repeated load triaxial test data on granular materials. The simpler K-θ model (see Fig. 2) often adequately captures the overall stress dependency (bulk stress effects) of unbound aggregate behavior under compression type field loading conditions. The universal model (Uzan *et al.* 1992) considers additionally the effects of shear stresses and handles very well the modulus increase (unbound aggregates) or decrease (fine-grained soils) with increasing stress states even for extension type field loading conditions.

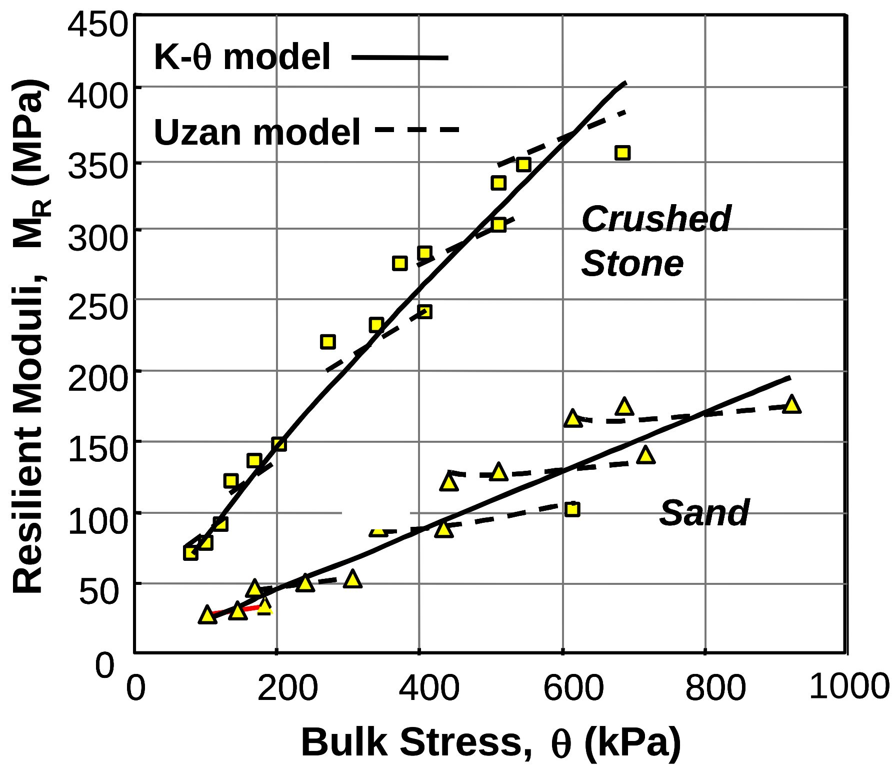

Fig. 2. Stress dependency of unbound granular materials.

The resilient modulus of fine-grained subgrade soils typically decrease at increasing stress levels thus exhibiting stress-softening type behavior. As a result, the most important parameter affecting the resilient modulus becomes the vertical deviator stress on top of the subgrade due to the applied wheel load. The bilinear or arithmetic model (Thompson and Elliott 1985) is a commonly used resilient modulus model for subgrade soils expressed by the modulus-deviator stress relationship given in Fig. 3.

As indicated by Thompson and Elliot (1985), the value of the resilient modulus at the breakpoint in the bilinear curve, E_{Ri}, (see Fig. 3) can be used to classify fine-grained soils as being soft, medium or stiff.

Some state highway agencies such as those in Illinois and Kentucky, have already established pavement design procedures based on mechanistic principles. For examples, the Illinois Department of Transportation (IDOT) mechanistic-empirical procedure is based on the ILLI-PAVE finite element solutions considering the nonlinear, stress-dependent stiffnesses of the unbound aggregate base and subgrade soil layers for designing full-depth and conventional asphalt pavements. It is important to note that the recently developed MEPDG has considerations for the most accurate level I material property inputs, which adequately emphasizes the importance of the nonlinear, stress-dependent resilient moduli. Such nonlinear, stress-dependent characterizations of geomaterial layer stiffnesses also need to be properly accounted for in the nondestructive

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evaluation of existing pavements, i.e. the backcalculation of layer moduli from FWD testing.

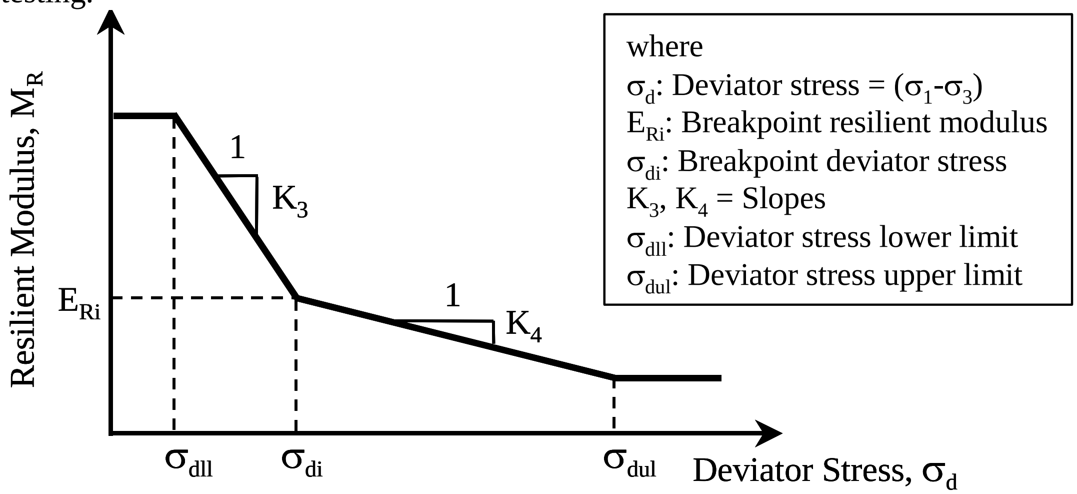

Fig. 3. Stress dependency of fine-grained soils characterized by bilinear model (after Thompson and Elliot, 1985).

4. ILLI-PAVE Pavement Structural Model

Developed at the University of Illinois, ILLI-PAVE (Raad and Figueroa 1980) is an axisymmetric FE program commonly used in the structural analysis of flexible pavements. The nonlinear, stress dependent resilient modulus geomaterial models summarized in the previous section are already incorporated into ILLI-PAVE. Numerous research studies have validated that the ILLI-PAVE model provides a realistic pavement structural response prediction for both highway and airfield pavements by incorporating stress-sensitive geomaterial models, the typical hardening behavior of nonlinear unbound aggregate bases and softening nature of subgrade soils under increasing stress states, and Mohr-Coulomb failure criteria to limit material strength (Garg *et al.* 1998, Thompson and Elliott 1985, Thompson 1992).

Recent research at the Federal Aviation Administration's Center of Excellence established at the University of Illinois also supported the development of a new, updated version of the program, now known as the ILLI-PAVE 2000 (Gomez-Ramirez *et al.* 2002). Among the several modifications implemented in the new ILLI-PAVE 2000 finite element code were: (1) increased number of elements (degrees of freedom); (2) new/updated material models for the granular materials and subgrade soils; (3) enhanced iterative solution methods; (4) Fortran 90 standard coding and compilation, and (5) a new user-friendly Microsoft Visual Basic/pre-post-processing interface to assist in the analysis.

The ILLI-PAVE finite element model, extensively tested and validated for over three decades, was therefore used in this study as an advanced structural model for solving flexible pavement surface deflections and other critical pavement stresses and strains under applied wheel loading. The goal was to establish a database of ILLI-PAVE response solutions that would eventually constitute the training and testing data sets for developing NN-based structural models for the rapid forward and backcalculation analyses of both conventional and full-depth asphalt pavements. For this purpose, a convergence study was performed to determine the domain size extent for the FE mesh discretization. A radial boundary placed at 25 times the contact area radius was sufficient to obtain convergence of deflections (Ceylan *et al.* 2004).

The Conventional Flexible Pavement (CFP) systems were modeled as three-layered axi-symmetric FE structures with an Asphalt Concrete (AC) surface course, an unbound aggregate base layer and the subgrade.

The top surface HMA was characterized as a linear elastic material with Young's Modulus, E_{AC}, and Poisson ratio, υ. Due to its simplicity and ease in model parameter evaluation, the K-θ model (Hicks and Monismith 1971) was used as the nonlinear characterization model for the unbound aggregate layer in the CFP. Based on the work of Rada and Witczak (1981) with a comprehensive granular material database, "K" and "n" model parameters can be correlated to characterize the nonlinear stress dependent behavior with only one model parameter using the following equation (Rada and Witczak 1981):

$$Log_{10}(K) = 4.657 - 1.807n \qquad (R^2 = 0.68;\ SEE = 0.22) \qquad (3)$$

Accordingly, good quality granular materials, such as crushed stone, show higher K and lower n values, whereas the opposite applies for lower quality aggregates. Following the study by Rada and Witczak (1981), the K-values used typically ranged from 20.7 MPa (3 ksi) to 82.7 MPa (12 ksi) and the corresponding n-values were obtained from Equation 3.

Fine-grained subgrade soils in the CFP were considered as "no-friction" but cohesion only materials and modeled using the bilinear or arithmetic model (see Fig. 3) for modulus characterization. The breakpoint deviator stress, E_{Ri}, was the main input for subgrade soils. The K_3 and K_4 slopes shown in Fig. 3 were taken as constants, 1,100 and 200, respectively, corresponding to medium soils given by Thompson and Elliott (1985). According to a comprehensive Illinois subgrade soil study by Thompson and Robnett (1979), the breakpoint deviator stress, σ_{di}, was taken as 41.4 kPa (6 psi) and 13.8 kPa (2 psi) was used for the lower limit deviator stress, σ_{dll}. The soil's unconfined compressive strength, Q_u, or cohesion was used to determine the upper limit deviator stress, σ_{dul}, (see Fig. 3) as a function of the breakpoint deviator stress, E_{Ri}, using the following relationship (Thompson and Robnett 1979):

$$\sigma_{dul}(psi) = 2 \times cohesion(psi) = Q_u(psi) = \frac{E_{Ri}(ksi) - 0.86}{0.307} \qquad (4)$$

Therefore, HMA modulus, E_{AC}, granular base K-θ model parameter K, and the subgrade soil break point deviator stress, E_{Ri}, in the bilinear model were used as the layer stiffness inputs for all the different CFP ILLI-PAVE runs.

The 40-kN (9-kip) wheel load was applied as a uniform pressure of 552 kPa (80 psi) over a circular area of radius 152 mm (6 in.). The thickness and moduli ranges used for the CFP are summarized in Table 1 (Ceylan *et al.* 2004).

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Table.1 Pavement geometry and material inputs for development of NN models.

Pavement Layer	Thickness (mm)	Layer modulus (MPa)	Poisson's ratio
Asphalt Concrete	76 to 381	690 – 13,800	0.35
Unbound Aggregate Base	102 to 559	K: 20 – 82	0.35
Subgrade	7,620 mm minus total pavement thickness	E_{Ri}: 7 – 96	0.45

5. NN Models for Flexible Pavement Systems

For the CFP systems, a total of 24,093 ILLI-PAVE FE runs were conducted by randomly choosing the pavement layer thicknesses and input variables within the given ranges in Table 1 to generate a knowledge database for NN trainings. The outputs recorded were the pavement surface deflection basin and the critical pavement responses, radial strain at the bottom of the AC layer (ε_{AC}), vertical strain on top of the subgrade (ε_{SG}), and the deviator stress on top of the subgrade layer (σ_D).

Backpropagation type neural networks were used to develop NN structural models for predicting the critical pavement responses (ε_{AC}, ε_{SG}, and σ_D) using the FWD deflection data. The FWD surface deflections (D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60}, and D_{72} – the subscript refers to offsets in inches at which the displacements are recorded) are often collected at several different locations, at the drop location (0) and at radial offsets of 203-mm (8-in.), 254-mm (12-in.), 457-mm (18-in.), 610-mm (24-in.), 914-mm (36-in.), 1219-mm (48-in.), 1524-mm (60-in.), and 1829-mm (72-in.). For the modeling work, surface deflections at these FWD sensor radial offsets were obtained from the ILLI-PAVE solutions and used as synthetic data to train NNs. The NN network architecture had 6 input variables (FWD deflections D_0, D_{12}, D_{24}, and D_{36}; and AC layer thickness (t_{AC}), granular base thickness (t_{GB})), two hidden layers with 60 hidden nodes in each layer, and 3 critical pavement responses, ε_{AC}, ε_{SG}, and σ_D, in the output layer. A neural network architecture with two hidden layers was exclusively chosen in accordance with the satisfactory results obtained previously with such networks considering their ability to better facilitate the nonlinear functional mapping (Ceylan 2002).

These NN models are referred to as "forward-calculation" models since they predict the critical pavement responses directly from the FWD deflections and layer thicknesses eliminating the need for first backcalculating the pavement layer moduli and inputting them into a structural model for computation of critical responses. The directness of this approach can save time and effort in analyzing structural adequacy of field pavement sections from FWD data. Once validated with field data, the NN model

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can predict ε_{AC} for AC fatigue condition evaluation and ε_{SG} or σ_D for rutting performance evaluation in the field.

Fig. 4 shows the training and testing MSE progress curves for the 6-60-60-3 network (6 input, 60 and 60 hidden, and 3 output nodes, respectively) for 6,000 learning cycles or training epochs. Figs. 5, 6, and 7 depict the prediction ability of the 6-60-60-3 network at the 6,000th training epoch. Average absolute errors (AAEs) were calculated as sum of the individual absolute errors divided by the 1,000 independent testing patterns. The AAE values from the NN predictions were 0.5% and 1.8% for ε_{AC} and ε_{SG}, respectively. The AAE value for the predicted subgrade deviator stresses (σ_D) was also 1.4%.

Similarly, NN models could be developed for predicting other critical pavement responses which are shown to be good layer condition indicators. For instance, the compressive strain on top of base layer is shown to be a good indicator for long-term performance as represented by base strength or rutting potential. Researchers have also shown, based on analysis of field measurements, that the quality of base layer has no significant effect on pavement surface deflections; it has, however, a significant effect on the long-term performance of the pavements. Thus, the compressive strain on top of the base layer could be predicted using the NN structural models based on the routinely collected FWD data and thus the base course performance could be assessed.

The performance of developed NN models was evaluated using actual field data acquired from Interstate I-35 near Clarke County in Iowa. The evaluated test section was a conventional flexible pavement with 406.4 mm (16 in.) of AC surface layer and 457.2 mm (18 in.) of unbound granular material. Figs. 8, 9, and 10 display the predictions of ε_{AC}, ε_{SG}, and σ_d, respectively along the pavement section based on FWD data acquired on May 3, 2005. The NN model predictions of critical pavement structural responses are consistent and as expected. Visual distress surveys conducted on these pavement sections showed that they were performing satisfactorily.

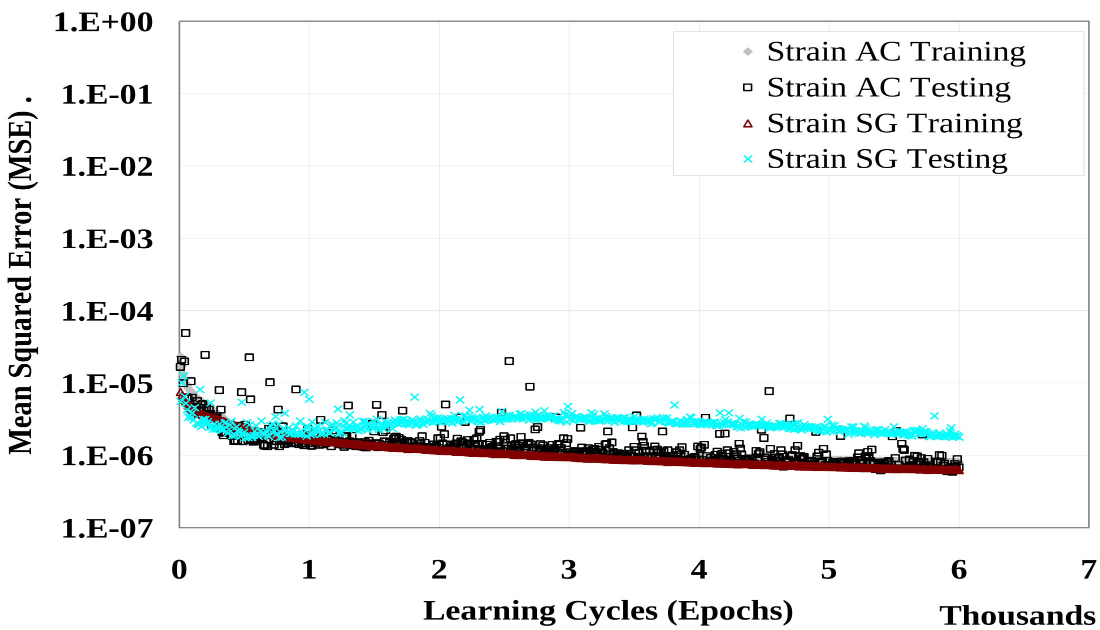

Fig. 4. Training progress of NN forward calculation models.

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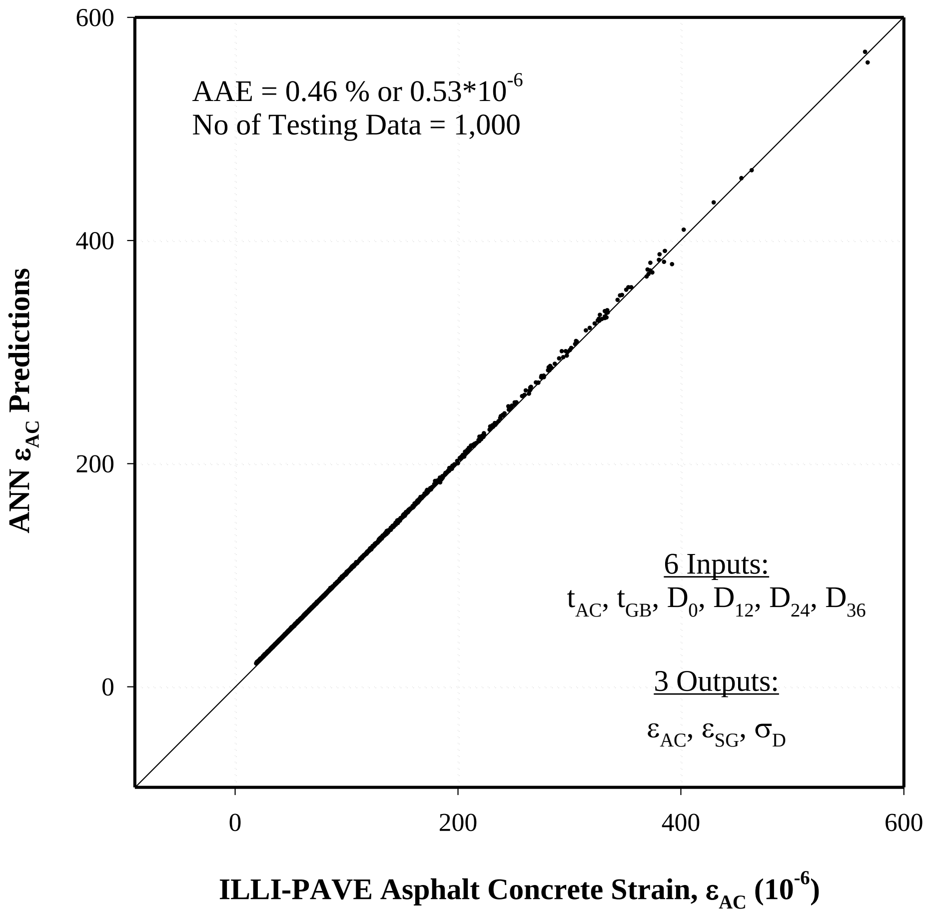

Fig. 5. AC strain (ε_{AC}) prediction performance of the 6-60-60-3 NN model.

Reference to this paper should be made as follows: Ceylan, H. and Gopalakrishnan, K. (2011). "*Computationally Efficient Surrogate Response Models for Mechanistic-Empirical Pavement Analysis and Design*". Structure and Infrastructure Engineering, Vol. 7, No. 4, pp.297 - 304.

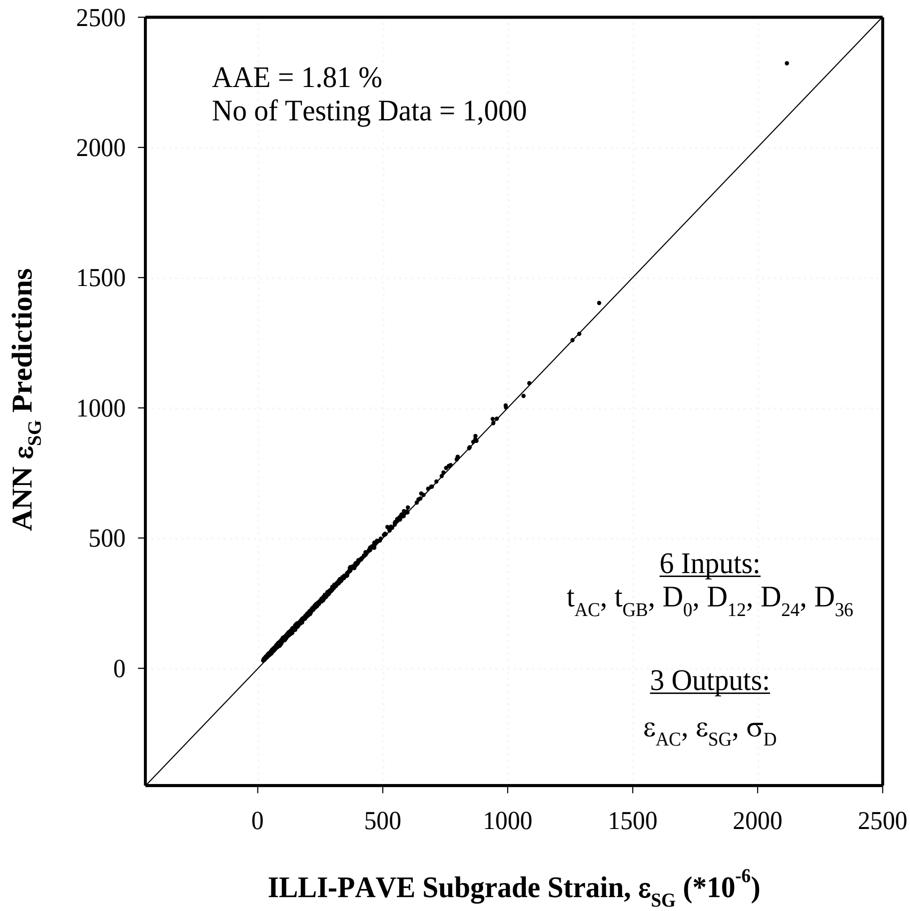

Fig. 6. Subgrade compressive strain (ε_{SG}) prediction performance of the 6-60-60-3 NN model.

Reference to this paper should be made as follows: Ceylan, H. and Gopalakrishnan, K. (2011). "*Computationally Efficient Surrogate Response Models for Mechanistic-Empirical Pavement Analysis and Design*". Structure and Infrastructure Engineering, Vol. 7, No. 4, pp.297 - 304.

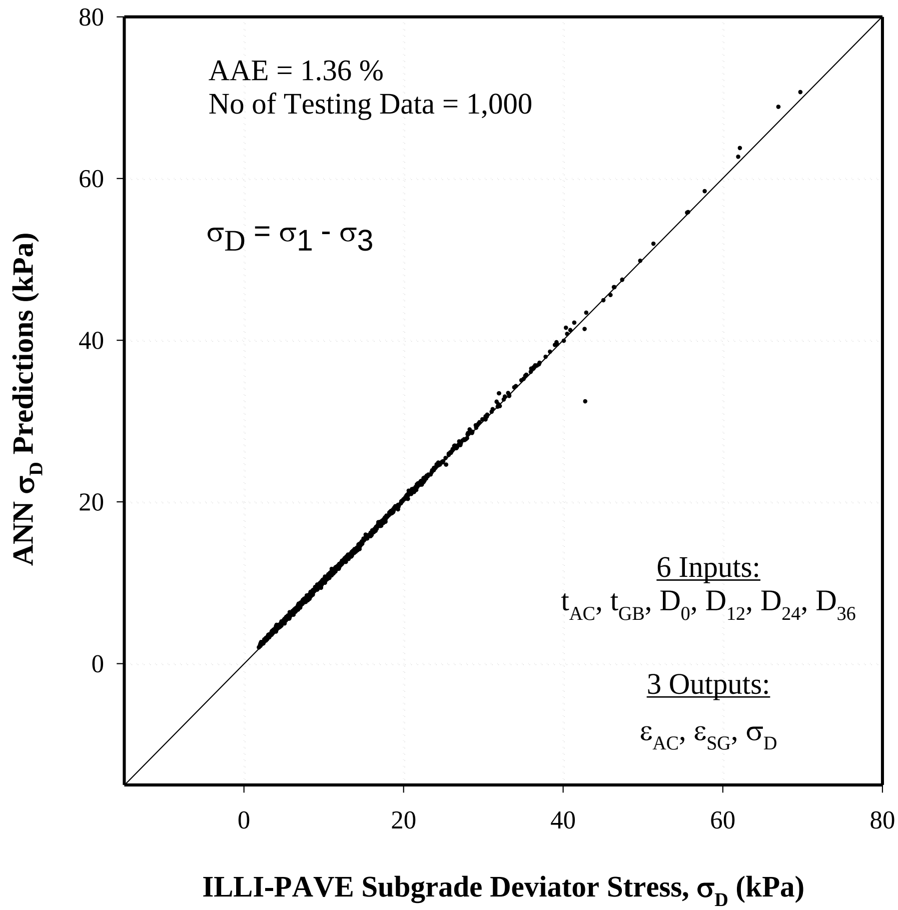

Fig. 7. Subgrade deviator stress (σ_d) prediction performance of the 6-60-60-3 NN model.

Reference to this paper should be made as follows: Ceylan, H. and Gopalakrishnan, K. (2011). "*Computationally Efficient Surrogate Response Models for Mechanistic-Empirical Pavement Analysis and Design*". Structure and Infrastructure Engineering, Vol. 7, No. 4, pp.297 - 304.

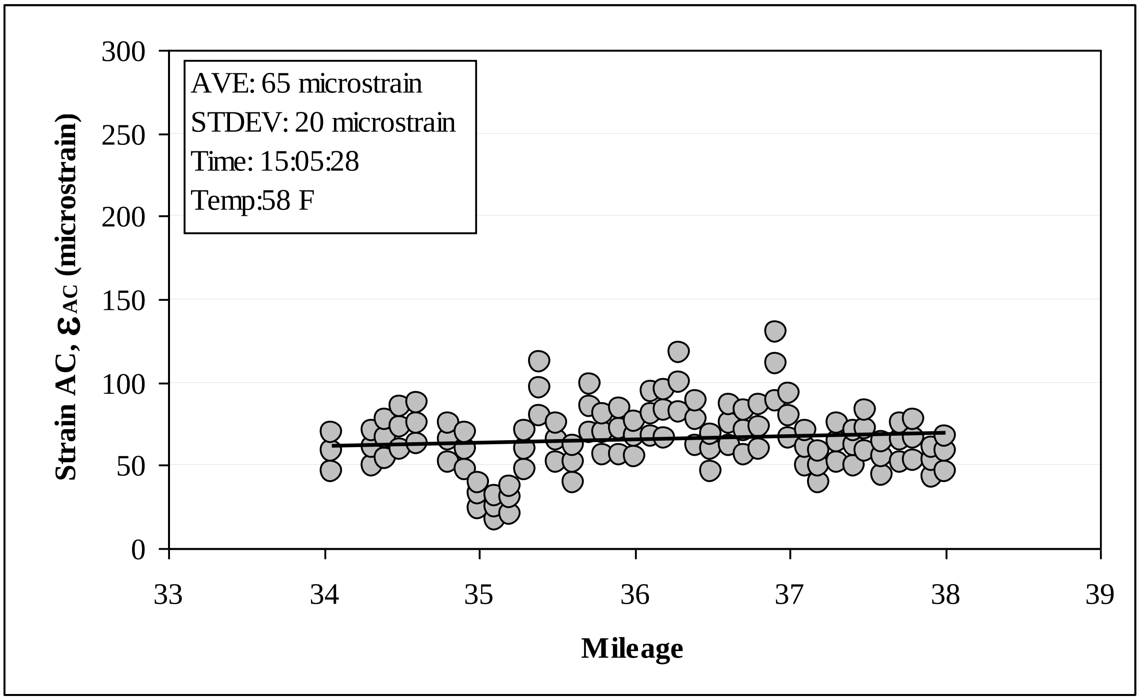

Fig. 8. Prediction of ε_{AC} along highway I-35 near Clarke County, Iowa.

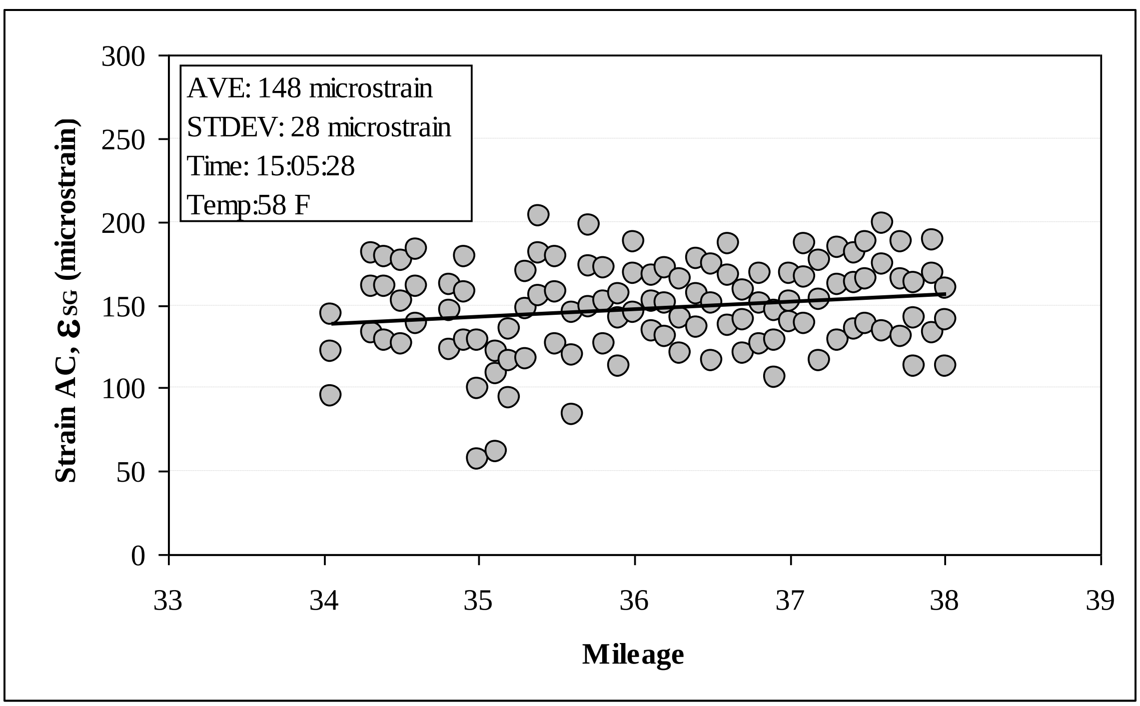

Fig. 9. Prediction of ε_{SG} along highway I-35 near Clarke County, Iowa.

Reference to this paper should be made as follows: Ceylan, H. and Gopalakrishnan, K. (2011). "*Computationally Efficient Surrogate Response Models for Mechanistic-Empirical Pavement Analysis and Design*". Structure and Infrastructure Engineering, Vol. 7, No. 4, pp.297 - 304.

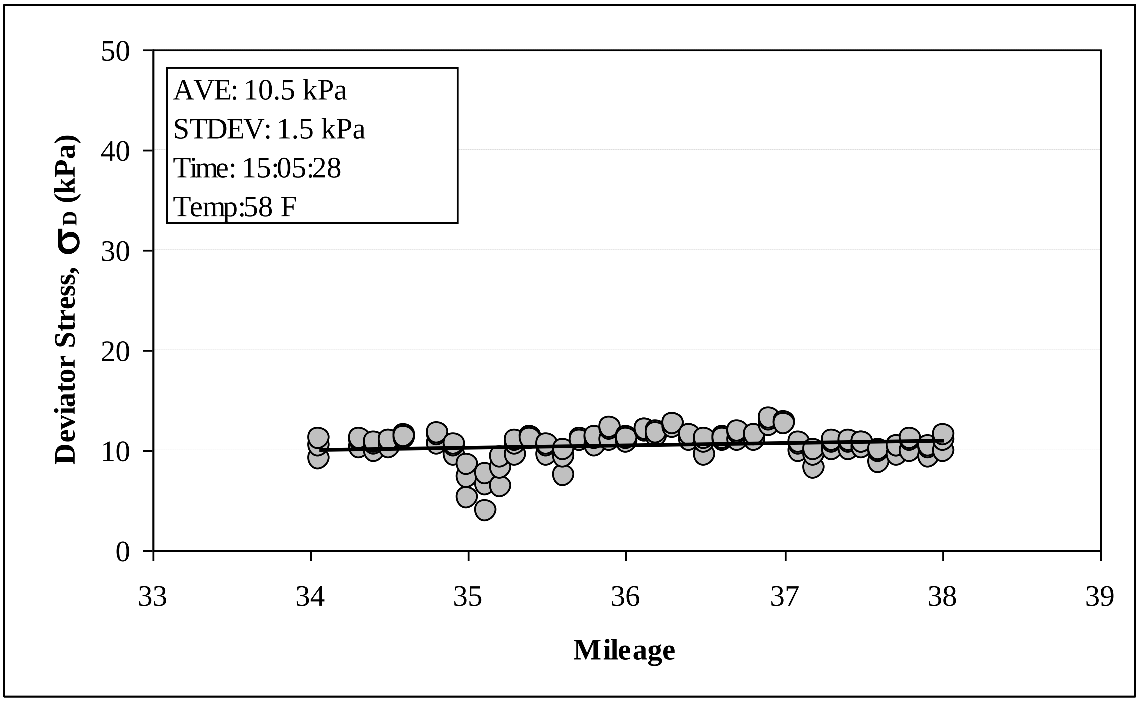

Fig. 10. Prediction of σ_d along highway I-35 near Clarke County, Iowa.

8. Summary and conclusions

Neural Networks (NN) based pavement structural models were proposed as surrogates for flexible pavement response analysis in the new Mechanistic Empirical Pavement Design Guide (MEPDG) developed for the American Association of State Highway and Transportation Officials (AASHTO). Unlike the linear elastic layered theory commonly used in pavement layer backcalculation, realistic nonlinear unbound aggregate base and subgrade soil modulus models were used in the ILLI-PAVE finite-element program to account for the typical stiffening behavior of unbound aggregate base and the fine-grained subgrade soil moduli decreasing with increasing stress states. The NN models successfully predicted the layer moduli and critical pavement responses computed by the ILLI-PAVE FE solutions.

It has been shown that NNs are capable of mapping complex relationships, such as those studied in complex finite element analyses, between the input parameters and the output variables for nonlinear, stress-dependent systems. Such NN-based structural models can provide pavement engineers and designers with sophisticated finite element solutions, without the need for a high degree of expertise in the input and output of the problem.

The NN approach has significant potential in the context of mechanistic-empirical pavement analysis and design. NN models trained over comprehensive datasets could be successfully incorporated into MEPDG as surrogates for pavement materials characterization models and pavement performance prediction models. Because NNs excel at mapping in higher-order spaces, such models can go beyond the existing univariate relationships between pavement structural responses and performance (e.x., subgrade strain criteria). NNs could be used to examine several variables at once and the interrelationships between them. NNs could also be used to develop models for distress phenomena such as thermal cracking, block cracking, and rutting in AC pavements, and faulting and D-cracking in concrete pavements.

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