

1 **Use of Artificial Neural Networks for Analyzing Full Depth Asphalt Pavements**

2 **ABSTRACT**

3 This paper describes the use of artificial neural networks (ANNs) as pavement structural analysis tools for the rapid
4 and accurate prediction of critical responses and deflection profiles of flexible pavements subjected to typical
5 highway loadings. The ILLI-PAVE finite element program, extensively tested and validated for over three decades,
6 was used as an advanced structural model for solving the critical responses of full depth flexible pavements. Unlike
7 the linear elastic layered theory commonly used in pavement layer backcalculation, nonlinear subgrade soil response
8 models were used in the ILLI-PAVE program to account for the softening nature of fine-grained subgrade soils
9 under increasing stress states. ANN models then trained with the results from the ILLI-PAVE solutions have been
10 found to be viable alternatives. The trained forward calculation ANN models were capable of predicting asphalt
11 tensile strains and subgrade compressive stresses/strains with low average absolute errors of those obtained directly
12 from the ILLI-PAVE analyses. ANN backcalculation models developed in this study were also capable of
13 successfully predicting the pavement layer moduli from the FWD deflection basins and they may be used in the field
14 for rapidly assessing the condition of the pavement sections during the FWD testing.

15 **Key Words:** Artificial Neural Networks, Falling Weight Deflectometer, Finite Element Analysis, Flexible
16 Pavements, Pavement Analysis and Design, Pavement Layer Backcalculation

1 INTRODUCTION

2 Elastic layered programs (ELPs) used in asphalt pavement analysis assume linear elasticity. Pavement
3 geomaterials do not, however, follow a linear type stress-strain behavior under repeated traffic loading. In effect,
4 nonlinear stress sensitive response of unbound aggregate materials and fine-grained subgrade soils has been well
5 established [1, 2, 3]. Unbound aggregates exhibit *stress hardening* and fine-grained soils show *stress softening* type
6 behavior. When these geomaterials are used as pavement layers, the layer stiffnesses, i.e., moduli are no longer
7 constant but functions of the applied stress state. Pavement structural analysis programs that take into account
8 nonlinear geomaterial characterization, such as the ILLI-PAVE finite element program [4], need to be employed to
9 more realistically predict pavement responses needed for mechanistic based pavement design.

10 Artificial neural networks (ANNs) are valuable computational tools that are increasingly being used to
11 solve resource-intensive complex problems as an alternative to using more traditional techniques. In a recent
12 successful application at the University of Illinois, Ceylan [5] employed ANNs in the analysis of concrete pavement
13 systems and developed ANN-based design tools that incorporated the state-of-the-art finite element solutions into
14 routine practical design at several orders of magnitude faster than those sophisticated finite element programs. In
15 another successful application, Meier et al. [6] trained backpropagation type ANNs as surrogates for ELP analysis in
16 a computer program for backcalculating pavement layer moduli and realized a 42 times increase in processing
17 speed. Similar ANN applications were also reported by Meier and Rix [7], Gucunski and Krstic [8], Khazanovich
18 and Roesler [9], and Kim and Kim [10]. The research project team working on the development of the new
19 mechanistic based AASHTO Pavement Design (NCHRP 1-37A) have also recognized ANNs as nontraditional, yet
20 very powerful computing techniques and took advantage of ANN models in preparing the 2002 Design Guide
21 concrete pavement analysis package.

22 Recent research studies at the Iowa State University and University of Illinois have focused on the
23 development of ANN based forward and backcalculation type flexible pavement analysis models to predict critical
24 pavement responses and layer moduli, respectively. In the field, the pavement deflection profiles are obtained from
25 Falling Weight Deflectometer (FWD) measurements, which require the use of backcalculation type structural
26 analysis to determine pavement layer stiffnesses and as a result estimate pavement remaining life. Although ANN
27 modeling was used in the past to aid in backcalculation [5], the structural models used to train the ANN models did
28 not account for realistic stress sensitive geomaterial properties. For this reason, ILLI-PAVE finite element program,
29 considering the nonlinear stress dependent geomaterial characterization, was utilized to generate a solution database
30 for developing ANN-based structural models to accurately predict pavement deflection basins, and pavement layer
31 moduli from realistic FWD deflection profiles. Such use of ANN models is described in this paper to enable
32 pavement engineers to easily and quickly incorporate the needed sophistication in structural analysis, such as from
33 finite element modeling with proper characterization of pavement layers, into routine practical design.

35 NONLINEAR GEOMATERIAL CHARACTERIZATION

36 Considering increased serviceability and performance requirements of today's pavements, the field stress
37 states, repeated application of moving traffic loads, field temperature and moisture are among the most important
38 factors to be correctly accounted for in pavement structural analysis. Under the repeated application of moving
39 traffic loads, most of the deformations are recoverable and thus considered elastic. It has been customary to use
40 resilient modulus (M_R) for the elastic stiffness of the pavement materials defined as the repeatedly applied wheel
41 load stress divided by the recoverable strain determined after shakedown of the material. Repeated load triaxial tests
42 are commonly employed to evaluate the resilient properties of unbound aggregate materials and cohesive subgrade
43 soils. Therefore, emphasis should be given in structural pavement analysis to realistic nonlinear material modeling
44 of the subgrade layers primarily based on repeated load triaxial test results [11].

45 The resilient modulus of fine-grained subgrade soils is dependent upon the stress state. Typically, soil
46 modulus decreases at increasing stress levels thus exhibiting stress-softening type behavior. As a result, the most
47 important parameter affecting the resilient modulus becomes the vertical deviator stress due to the applied wheel
48 load. The bilinear or arithmetic model [2] is a commonly used resilient modulus model for subgrade soils expressed
49 by the modulus-deviator stress relationship given in FIGURE 1. As indicated by Thompson and Elliot [2], the value
50 of the resilient modulus at the breakpoint in the bilinear curve, E_{Ri} , can be used to classify fine-grained soils as being
51 soft, medium or stiff.
52

1 ILLI-PAVE FINITE ELEMENT MODEL

2 ILLI-PAVE, an axi-symmetric finite element program, extensively tested and validated for over three
3 decades, was used as an advanced structural model for solving the pavement surface deflections and critical stresses
4 and strains for flexible pavement sections. The ILLI-PAVE model was used to develop the Illinois Department of
5 Transportation's (ILDOT) Full-Depth Asphalt Concrete Thickness Design Procedure. The ILLI-PAVE model
6 incorporates stress-sensitive material models, the typical hardening behavior of nonlinear unbound aggregate bases
7 (UAB) and softening nature of subgrade soils under increasing stress states, and Mohr-Coulomb failure criteria to
8 limit material strength. Thus, ILLI-PAVE model indicating the non-linear representation of the pavement systems is
9 selected to create ANN training set. The goal was to establish a database composed of pavement and loading input
10 properties together with the corresponding ILLI-PAVE 2000 (an advanced version of the ILLI-PAVE model)
11 response solutions that would eventually constitute the training and testing data sets needed in the development of
12 ANN-based structural models for the rapid forward- and back-calculation analysis of full depth flexible pavements.

13 ILLI-PAVE model was developed at the University of Illinois [4] based on the finite element code used by
14 Duncan et al. [12] for highway pavement analysis. Since then, numerous research studies have demonstrated that
15 the ILLI-PAVE model provides a realistic pavement structural response prediction for highway and airfield
16 pavements [2, 3, 13, and 14]. Recent research studies at the Federal Aviation Administration's Center of Excellence
17 established at the University of Illinois also supported the development of a new, updated version of the program,
18 now known as the ILLI-PAVE 2000 [15]. Among the several modifications implemented in the new ILLI-PAVE
19 2000 finite element code were: (1) increased number of elements (degrees of freedom); (2) new/updated material
20 models for the granular materials and subgrade soils; (3) enhanced iterative solution methods; (4) Fortran 90
21 standard coding and compilation, and (5) a new user-friendly Microsoft Visual Basic pre-/post-processing interface
22 to assist in the analysis.

23 Generating ILLI-PAVE 2000 Finite Element Solution Database

24 The full depth flexible pavement systems were constructed by placing one or more layers of hot mix asphalt (HMA)
25 directly on the subgrade. For this analysis, an HMA with a thickness varying between 152 mm (6 in.) and 610 mm
26 (24 in.) over a subgrade with a total thickness of about 9,144 mm (360 in.) was selected as the pavement system.
27 The asphalt surface layer was characterized as a linear elastic material modeling with E_{AC} , and Poisson's ratio, ν .
28 The asphalt concrete (AC) layer modulus were kept between the realistic range of 690 MPa (100 ksi) and 20,685
29 MPa (3,000 ksi), and the Poisson's ratio was taken constant as 0.35.

30 Fine-grained soils were considered as "no-friction" but cohesion only materials and modeled using the
31 bilinear or arithmetic model (see FIGURE 1) for modulus characterization. The breakpoint deviator stress E_{Ri} , was
32 the main input for subgrade soils. The K3 and K4 slopes were taken as constants, 1,100 and 200, respectively,
33 corresponding to medium soils given by Thompson and Elliott [2]. According to a comprehensive Illinois subgrade
34 soil study by Thompson and Robnett [16], the breakpoint deviator stress, σ_{di} , was taken as 41.4 kPa (6 psi) and 13.8
35 kPa (2 psi) was used for the lower limit deviator stress, σ_{dli} . The Poisson's ratio was assumed to be 0.45 for the fine-
36 grained subgrade layer. The soil's unconfined compressive strength, Q_u , or cohesion was used to determine the
37 upper limit deviator stress, σ_{dul} , (see FIGURE 1) as a function of the breakpoint deviator stress, E_{Ri} , using the
38 following relationship [16]:
39

$$40 \sigma_{dul} (psi) = 2.2 \times cohesion (psi) = Q_u (psi) = \frac{E_{Ri} (ksi) - 0.86}{0.307}$$

41
42 The wheel load level assigned for pavement system was 40-kN (9-kip) and applied as a uniform pressure of
43 552 kPa (80 psi) over a circular area of radius 152 mm (6 in.) as shown in FIGURE 2. To generate a ILLI-PAVE
44 2000 solution database, a uniform random number generator was utilized to obtain values for each independent
45 variable of AC thicknesses (h_{AC}), AC moduli (E_{AC}), and the breakpoint deviator stress (E_{Ri}). A total of 2,000 input
46 files were generated and the corresponding pavement layer model parameters for the subgrade layer were calculated
47 using the randomly selected E_{Ri} values. The ILLI-PAVE 2000 pavement geometry and material model inputs are
48 given in TABLE 1.

49 The finite element mesh used for generating the ILLI-PAVE runs is shown in FIGURE 3. The mesh
50 consisted of 600 elements. Meshing was determined according to the stress concentration effect and FWD sensor
51 locations. Therefore, a fine mesh was used under the FWD loading where the highest stress concentration occurs.
52 The horizontal mesh size was arranged to match the FWD sensor distances. An aspect ratio of one or close to one
53 was selected for high stress concentration areas. The total analysis depth of the pavement was taken as 9,144 mm

1 (360 in.). The radial boundary of the mesh was placed at the 30 times the contact area radius and past studies [19]
2 indicate that this distance is enough to obtain convergence of the deflections. Also, a standard, fine mesh was used
3 consisting of 50.8 mm (2 in.) thick elements within the top 1,016 mm (40 in.) thick section of the pavements. Thus,
4 a standard finite element mesh was used for all ILLI-PAVE runs.

5 A total of 2,000 ILLI-PAVE analyses were performed in the following manner: For each ILLI-PAVE run,
6 the input variables for AC layer thickness (h_{AC}), AC layer elasticity modulus (E_{AC}), and the subgrade layer E_{Ri} value
7 were recorded along with the pavement responses of surface deflections (D_0 , D_8 , D_{12} , D_{18} , D_{24} , D_{36} , D_{48} , D_{60} , and
8 D_{72} , see FIGURE 4) and the critical pavement responses of horizontal strain (ϵ_{AC}) at the bottom of the AC layer,
9 vertical, compressive strain (ϵ_{SG}) on top of the subgrade, and the deviator stress (σ_D) on top of the subgrade layer at
10 the center line of the modeled FWD loading were recorded (see FIGURE 2). AC layer thicknesses were kept
11 between 152 mm (6 in.) and 610 mm (24 in.), considering that most full depth flexible pavement design thicknesses
12 would fall in this range. In a similar way, the AC layer modulus were kept between the realistic range of 690 MPa
13 (100 ksi) and 20,700 MPa (3,000 ksi), and the subgrade E_{Ri} value were kept between 6.9 MPa (1 ksi) and 103.5 MPa
14 (15 ksi).
15

16 ARTIFICIAL NEURAL NETWORKS (ANNs) AS PAVEMENT ANALYSIS TOOLS

17 Backpropagation type artificial neural network models were trained in this study with the results from the
18 ILLI-PAVE finite element program and were used as analysis design tools for predicting stresses, strains and
19 deflections for full depth flexible pavement systems. Backpropagation type ANNs are very powerful and versatile
20 networks that can be taught a mapping from one data space to another using examples of the mapping to be learned.
21 The term “backpropagation network” actually refers to a multi-layered; feed-forward neural network trained using
22 an error backpropagation algorithm. The learning process performed by this algorithm is called “backpropagation
23 learning” which is mainly an “error minimization technique” [17]. As with many ANNs, the connection weights in
24 the backpropagation ANNs are initially selected at random. Inputs from the mapping examples are propagated
25 forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct
26 answers are then propagated backwards through the network and the connection weights are individually adjusted to
27 reduce the error. After many examples (training patterns) have been propagated through the network many times,
28 the mapping function is learned with some specified error tolerance. This is called supervised learning because the
29 network has to be shown the correct answers for it to learn. Backpropagation networks excel at data modeling with
30 their superior function approximation capabilities [17].

31 Training Set Generation

32 A total of 2,000 of ILLI-PAVE analysis results were used for generating ANN training and testing sets. Two types
33 of neural network models were designed; Forward calculation models (FCMs) and Backcalculation models (BCMs).
34 Each model had its own training and testing sets prepared from the ILLI-PAVE 2000 solution database. Training
35 sets for the forward calculation models consisted of the input layer parameters of E_{AC} , E_{Ri} , and h_{AC} . The network
36 output layer variables were the pavement surface deflections of D_0 , D_8 , D_{12} , D_{18} , D_{24} , D_{36} , D_{48} , D_{60} , and D_{72} (FCM-1),
37 and the critical pavement responses of ϵ_{AC} , ϵ_{SG} , and σ_D (FCM-2). For the first backcalculation model (BCM-1),
38 training and testing sets had five input parameters of D_0 , D_{12} , D_{24} , D_{36} and h_{AC} and two output variables of E_{AC} and
39 E_{Ri} . The second backcalculation model (BCM-2) had the same input parameters as in BCM-1 and the three output
40 variables consisted of the critical pavement responses of ϵ_{AC} , ϵ_{SG} , and σ_D . In addition to the training and testing sets
41 prepared for BCM-1 and BCM-2, four more ANN training sets were generated by introducing 10% ($\pm 5\%$) and 20%
42 ($\pm 10\%$) noise to the FWD deflection values used in both backcalculation models. The purpose of introducing noisy
43 patterns in the training sets was to develop a more robust network that can tolerate the noisy or inaccurate deflection
44 patterns collected from the FWD deflection basins. The addition of noise was conducted as follows: The 2,000 ILLI-
45 PAVE solution database was first initially partitioned to create a training set of 1,800 patterns and an independent
46 testing set of 200 patterns to check the performance of the trained ANN models. 1,800 uniformly distributed random
47 numbers ranging from 0 to $\pm 5\%$ for low-noise patterns and another 1,800 set ranging from 0 to $\pm 10\%$ for high-noise
48 patterns were generated each time to create noisy training patterns. After adding 1,800 randomly selected noise
49 values only to the pavement surface deflections of D_0 , D_{12} , D_{24} , and D_{36} , a new training data set was developed for
50 each noisy training set. By repeating the noise introduction procedure, four more training data sets were formed.
51 Including the original training set with no noise in it, a total of 9,000 patterns were used to train the noise-introduced
52 ANN backcalculation models of BCM-1 and BCM-2. The input parameters for each training set were normalized

1 between +2 and -2, and the output variables were normalized between 0.1 and 0.9. All training data sets were
2 randomly shuffled before the ANN trainings.

3 **Forward Calculation Models**

4 Backpropagation type neural network models were designed to develop ANN-based tools for predicting the critical
5 pavement responses and pavement surface deflections based on the known pavement layer moduli and AC layer
6 thickness. Since the pavement responses were calculated from the known pavement layer parameters, these ANN
7 models were named as the forward calculation models (FCMs). In forward calculation model no 1 (FCM-1), the
8 network input layer consisted of AC layer thickness (h_{AC}), and the moduli parameters of E_{AC} and E_{Ri} . The output
9 variables of this model are the pavement surface deflections at several different offsets (D_0 , D_8 , D_{12} , D_{18} , D_{24} , D_{36} ,
10 D_{48} , D_{60} , and D_{72}). Similar to the FCM-1, a second forward calculation model (FCM-2) was developed using the
11 same input parameters of h_{AC} , E_{AC} and E_{Ri} . FCM-2 output layer consisted of the critical pavement responses of two
12 strains (ϵ_{AC} and ϵ_{SG}) and the deviator stress (σ_D) under the standard 40 kN (9-kips) FWD loading. ANN training and
13 testing sets to develop these models were generated as explained before. The main advantage of the FCMs are the
14 ability to map the complex relationship between the input parameters (pavement layer moduli and thickness) and the
15 ILLI-PAVE finite element model outputs (pavement surface deflections and the critical pavement responses) and be
16 able to rapidly (in real time!; 50,000 predictions in one second using a personal computer with 2 GHz
17 microprocessor) produce these pavement responses as ANN model outputs. FIGURE 5 and FIGURE 6 show the
18 prediction performance of the FCM-1 and FCM-2. Note the very low average absolute error (AAE) values and the
19 excellent performance of the ANN FCM-1 and FCM-2.

20 **Backcalculation Models**

21 Several neural network architectures were designed and trained for predicting the magnitudes of the pavement layer
22 moduli (E_{AC} and E_{Ri}) and the critical pavement responses (ϵ_{AC} , ϵ_{SG} , and σ_D) using the FWD deflection data and the
23 AC layer thickness. Two of these models were used in this study. The first backcalculation model (BCM-1), was
24 designed to predict the moduli of the AC layer (E_{AC}) and the break-point modulus of the subgrade layer (E_{Ri}) using
25 only four of the FWD deflections of D_0 , D_{12} , D_{24} , and D_{36} placed at a standard spacing of 305 mm (12 in.) and the
26 AC layer thickness of h_{AC} . The designed network has 5 input parameters in the input layer and 2 output variables
27 (E_{AC} and E_{Ri}) in the output layer.

28 To train the ANN BCM-1, a training data file was formed using the 2,000 ILLI-PAVE runs mentioned
29 above. 200 of these runs were reserved as an independent testing set to confirm the proper training and to validate
30 the performance of the trained ANN model. A network with two hidden layers was exclusively chosen for the BCM-
31 1 trained in this study. Satisfactory results were obtained in the previous studies with these types of networks due to
32 their ability to better facilitate the nonlinear functional mapping [5].

33 Several network architectures with two hidden layers were trained for predicting the properties of the
34 pavement layer moduli with 5 input nodes and 2 output nodes. FIGURE 7a presents the training and testing mean-
35 squared errors (MSEs) of the 2 output responses obtained for the best network architecture at the end of 10,000
36 training epochs. Overall, the MSEs decreased as the networks grew in size with increasing number of neurons in the
37 hidden layers. The testing MSEs for the two output variables were, in general, slightly lower than the training ones.
38 The error levels for both training and testing sets matched closely when the number of hidden nodes approached 60
39 in the 5-60-60-2 architecture (5 inputs, 60 nodes in the 1st and 2nd hidden layers, and 2 output nodes, respectively).
40 The lowest training MSEs in the order of 1×10^{-4} (corresponding to a root mean squared error, RMSE, of 1%) were
41 obtained with the 5-60-60-2 architecture for both output variables.

42 The 5-60-60-2 architecture was chosen as the best architecture for the BCM-1 based on its lowest training
43 and testing MSEs. FIGURE 7a shows the training and testing MSE progress curves for the 5-60-60-2 network. Both
44 the training and testing curves for each of the outputs are in the same order of magnitude thus depicting proper
45 training. The almost constant MSEs obtained for the last 6,000 epochs (see FIGURE 7b) also provided a good
46 indication of adequate training for this network. FIGURE 7a depicts the prediction performance of the 5-60-60-2
47 network at 10,000 learning cycles. Average absolute errors (AAEs) were calculated as sum of the individual
48 absolute errors divided by the 200 independent testing patterns. The AAE for the AC layer moduli was 1.7% while
49 the AAE for the subgrade break-point moduli (E_{Ri}) was 2.5%. As shown in FIGURE 7b, all ANN predictions for the
50 200 independent testing set fall on the line of equality for the two pavement layer moduli thus indicating a proper
51 training and excellent performance of the ANN model.

52 Similar to the design and development of the backcalculation model BCM-1, a second backcalculation
53 model (BCM-2) was developed to predict the critical pavement responses of ϵ_{AC} , ϵ_{SG} , and σ_D directly from the FWD
54 deflection data. This approach eliminates the need of first predicting the pavement layer moduli and then using a

1 forward calculation engine to compute the critical pavement responses needed for pavement analysis and design.
2 The directness of this approach saves invaluable time in analyzing the pavement sections using the FWD deflection
3 basins. BCM-2 network architecture had 5 input parameters (similar to the BCM-1) and 3 output variables of
4 critical pavement responses in the output layer. After trying several different network architectures, the 5-60-60-3
5 network architecture produced the best results with very low training and testing MSEs after 10,000 learning cycles.
6 The AAE values were 1.1% for predicting the critical tensile strains at the bottom of the AC layer (ϵ_{AC}) and 0.7% for
7 predicting the critical compressive strains on top of the subgrade layer (ϵ_{SG}). The AAE value for the critical deviator
8 stresses on top of the subgrade layer was 0.1% (see FIGURE 8). Low error values indicate the proper training and
9 prediction performance of the ANN backcalculation models developed in this study.

10 BCM-1 and BCM-2 were then trained with the noisy training sets. The goal was to develop more *robust*
11 ANN models that can analyze the *imperfect* FWD deflection basins. A series of sensitivity analyses showed that
12 both BCM-1 and BCM-2 are sensitive to the even very small amount of changes in the four deflection values used to
13 train them. Therefore, it was decided to introduce different level of noise (10% and 20%) to the four FWD deflection
14 values used to train the backcalculation models. Robust networks can also tolerate the differences between the actual
15 field values and the fixed material property values assigned for AC and subgrade layers in the ILLI-PAVE 2000
16 model. Because of the noise introduction, the 200 independent testing data had more scatterings around the line of
17 equality and both the MSE and AAE values were increased for the robust ANN models (see FIGURE 9). But the
18 confidence interval of data is increased. The AAE values were only increased from 1.7% to 2.7% in BCM-1 for 10%
19 noise level, and from 1.7% to 4.9% for 20% noise level for predicting the AC layer moduli. FIGURE 9a and
20 FIGURE 9b show the performance of noise-introduced robust networks for predicting the layer moduli of full-depth
21 flexible pavement systems. Considering the 10% and 20% high level of noise introduced to the FWD deflection
22 data, the performance of the robust backcalculation models can be considered excellent indicating the power of
23 ANN methodology implemented in this study. When analyzing the FWD field data using the backcalculation
24 models developed in this study, it is suggested to consider at least 2-3% of noise in the deflection basins instead of
25 using backcalculation models that have no noise in them. Selecting the appropriate level of noise depends on the
26 quality of the FWD data. Factors such as surface conditions of the pavement, the “overall condition” of the FWD
27 machine used to collect the deflection data, and the reasonableness of the backcalculated modulus values are
28 important factors to consider.

29 **Processing Speed**

30 Comparison of the computation time required for the predictions of the ANN models and the ILLI-PAVE
31 2000 FE model solutions has shown that the ANN models developed in this study are about 2 million times faster
32 than the ILLI-PAVE 2000 FE model. The required time for preparing the input data files and post processing the
33 results from the finite element output files are not included in this comparison. For a large number of analyses to be
34 performed, the time saved using the ANN models can be invaluable to the pavement engineer when evaluating
35 hundreds or thousands of “what if” scenarios or when analyzing a large number of FWD data for a network level
36 testing. The rapid prediction ability of the ANN backcalculation models makes them perfect tools for analyzing the
37 FWD deflection data, and thus assessing the condition of the pavement sections, in real time during the field tests.
38

39 **PERFORMANCE OF ANN BASED STRUCTURAL MODELS USING FIELD DATA**

40 The primary objective in this study was to demonstrate that ANN models could be developed to perform
41 rapid predictions of pavement layer moduli and critical pavement responses from the FWD deflection basins for a
42 number of pavement input parameters considered in pavement analysis and design. The ANN models described
43 above successfully predicted the pavement layer moduli and critical pavement responses obtained from the ILLI-
44 PAVE 2000 finite element model and thus satisfied the main objective in this study. The ANN models developed
45 were meant to provide pavement design engineers with necessary tools to analyze the large number of pavement
46 sections and FWD deflection basins needed for routine pavement evaluation practices. It is therefore necessary to
47 demonstrate how these ANN models can successfully be used in project specific flexible pavement problems, once
48 an ANN-based methodology is adopted and implemented for analysis and design.

49 This section presents the concept of using an ANN-based methodology for analyzing flexible pavement
50 sections based on the FWD field deflection data. Pavement layer moduli and critical pavement responses predicted
51 by the ANN models were compared to the predictions from the ILLI-PAVE based algorithms. Thompson [18]
52 developed algorithms and charts (see FIGURE 11) based on the ILLI-PAVE finite element solutions. According to
53 these algorithms, E_{AC} and E_{Ri} values can be calculated from pavement surface deflections for a given AC layer

1 thickness with coefficient of correlation (R^2) values greater than 0.98. Following relationships were used for
 2 calculating the pavement layer moduli values provided by Thompson [18];

$$3 \quad \text{AREA} = 6 (D_0 + 2 D_{12} + 2 D_{24} + D_{36}) / D_0 \text{ (in.)}$$

$$4 \quad E_{AC} = 10^{1.85 - (4.90 * \text{LOG}(\frac{D_0 - D_{12}}{D_0}))} + 5.19 \text{ LOG}(D_0 - D_{24}) - 1.28 \text{ LOG}(D_{12} - D_{36}) \text{ (ksi)}$$

$$5 \quad E_{Ri} = 24.7 - 5.41 D_{36} + 0.31 D_{36} D_{36} \text{ (ksi)}$$

6
 7
 8 Three full-depth flexible pavement sections selected for field validation were Staley Road, Windsor Road
 9 and Carlyle Road (sections K and M2) sections located in Illinois. All of the sections were tested with a standard 9-
 10 kip plate load. Pavement layer properties for these sections are as follows. Staley road has an AC layer thickness of
 11 12 in. on top of a 12 in. lime modified subgrade. Deflections were obtained from FWD tests conducted in March 29,
 12 2000. The pavement temperature was 51 °F. The Windsor Road nondestructive test (NDT) data were collected in
 13 May 18, 1994. Pavement temperature was 70 °F. For Carlyle section K, the AC layer is 9.1 in. thick and in section
 14 M2 it is 11.5 in thick. The Carlyle pavement temperatures at the multiple testing times ranged from 61°F to 96 °F.

15 Four pavement surface deflections of D_0 , D_{12} , D_{24} , and D_{36} and AC layer thickness (h_{AC}) of these three field
 16 sites were used in the ANN BCM-1 to predict the E_{AC} and E_{Ri} values. Same FWD deflection data were then used in
 17 ILLI-PAVE based algorithms provided above and the calculated moduli values were compared with the ANN
 18 predictions and the results are presented in FIGURE 10. Note that ANN BCM-1 predictions and layer moduli values
 19 calculated from the ILLI-PAVE based algorithms agree well with each other (see FIGURE 10). The differences in
 20 the moduli predictions can be attributed to the different methodologies used in predicting the layer moduli and the
 21 number of ILLI-PAVE finite element solutions used to develop the ANN-based backcalculation models and the
 22 ILLI-PAVE based algorithms.
 23

24 SUMMARY & CONCLUSIONS

25 The ANN-based backcalculation and forward calculation models were developed in this study using 2,000
 26 ILLI-PAVE finite element solutions with nonlinear, stress-dependent pavement layer properties. Unlike the linear
 27 elastic layered theory commonly used in pavement layer backcalculation, realistic subgrade soil modulus models
 28 were used in the ILLI-PAVE program to account for the typical softening behavior of the fine-grained subgrade
 29 soils. The developed forward- and back-calculation ANN models successfully predicted the pavement layer moduli,
 30 critical pavement responses, and pavement surface deflections obtained from the ILLI-PAVE 2000 finite element
 31 solutions. ANN predictions had very low average absolute errors even for noisy deflection basins when compared to
 32 the ILLI-PAVE 2000 solutions. It was shown that ANNs are capable of mapping complex relationships between the
 33 input parameters and the output variables even for nonlinear, stress dependent systems. Such ANN-based structural
 34 analysis models can provide pavement engineers and designers with sophisticated finite element solutions, without
 35 the need for a high degree of expertise in the input and output of the problem. ANN models can rapidly (in real
 36 time!) output the required solutions in analyzing a large number of pavement deflection basins needed for routine
 37 pavement evaluation both for project specific and network level FWD testing. The rapid prediction ability of the
 38 ANN backcalculation models makes them perfect tools for analyzing the FWD deflection data, and thus assessing
 39 the condition of the pavement sections, in real time during the field tests.

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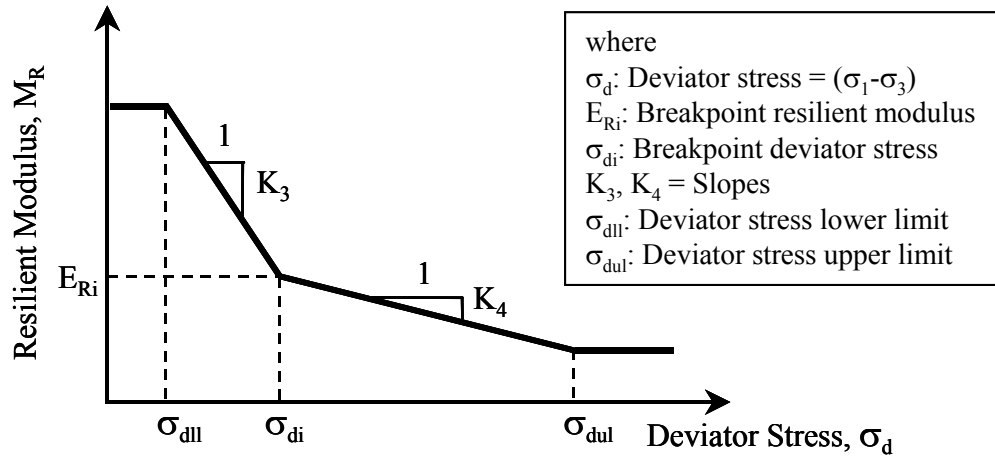


FIGURE 1 Stress Dependency of Fine-Grained Soils Characterized by Bilinear Model

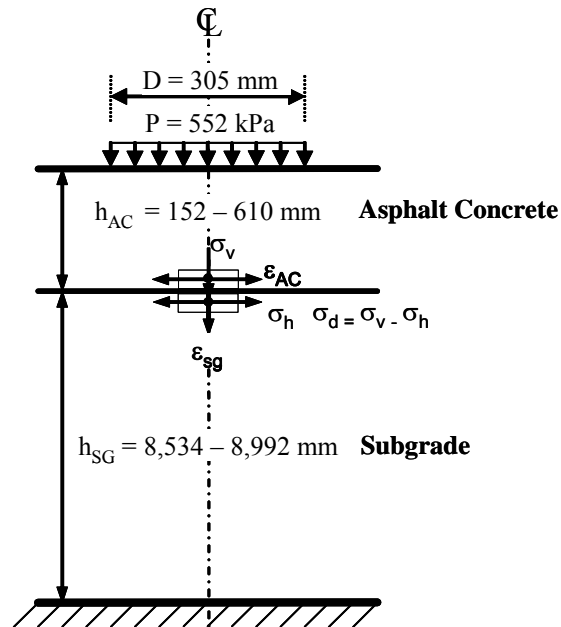


FIGURE 2 Layout of the Pavement Sections Analyzed

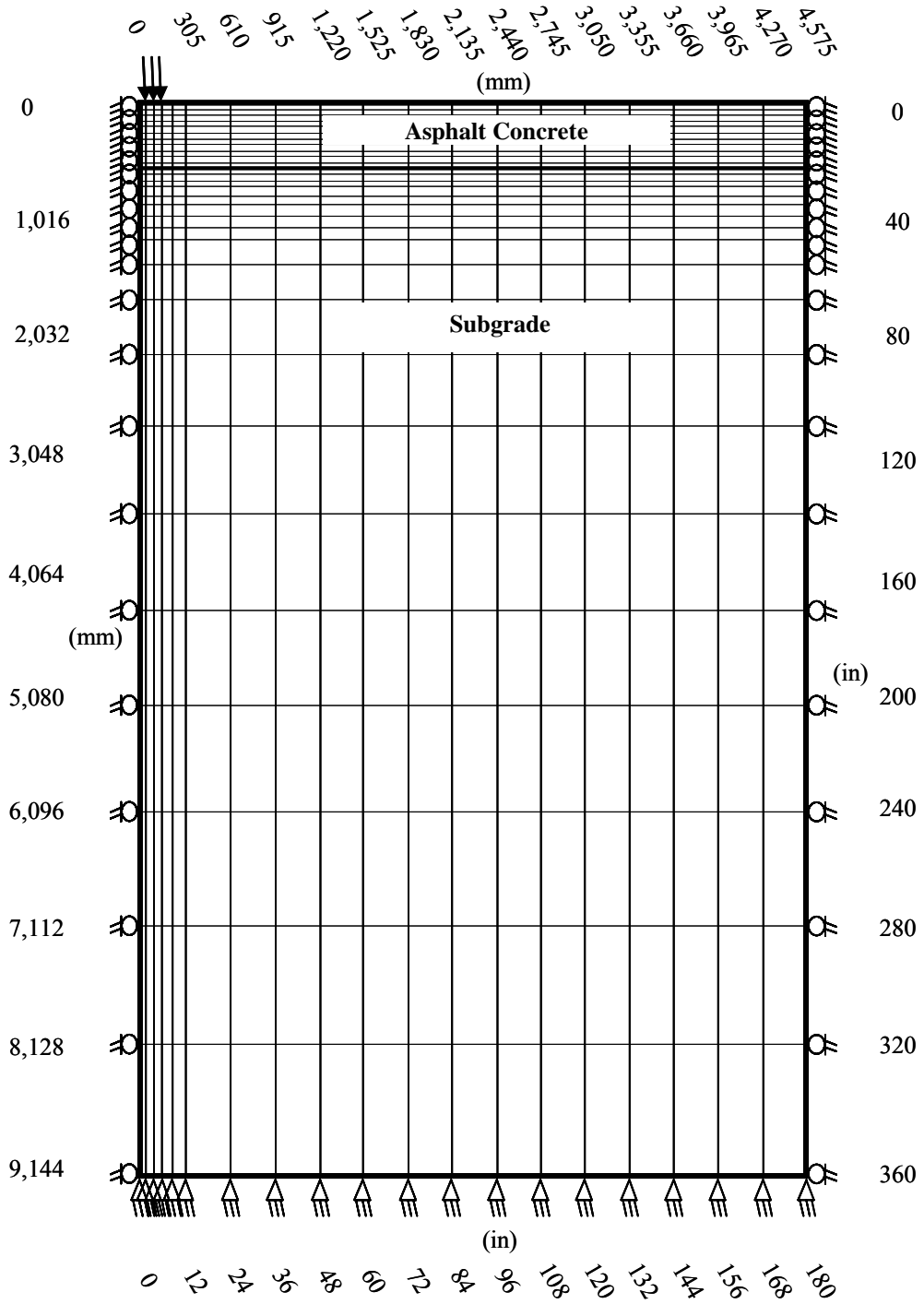


FIGURE 3 Pavement Geometry and Finite Element Mesh Used for Generating the ILLI-PAVE Runs

Sensor Offsets

Sensor Arrangement	(mm)	0	203	305	457	610	915	1,220	1,525	1,830
	(in)	0	8	12	18	24	36	48	60	72
Uniform Spacing		✓		✓		✓	✓	✓	✓	✓
SHRP Specification		✓	✓	✓	✓	✓			✓	

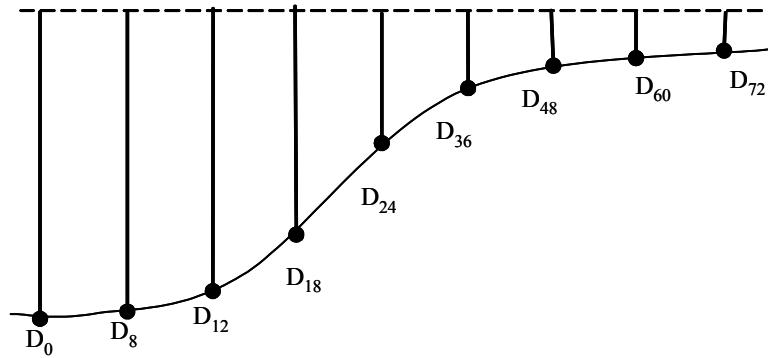


FIGURE 4 FWD Sensor Spacings and Schematic View of the FWD Deflection Basin

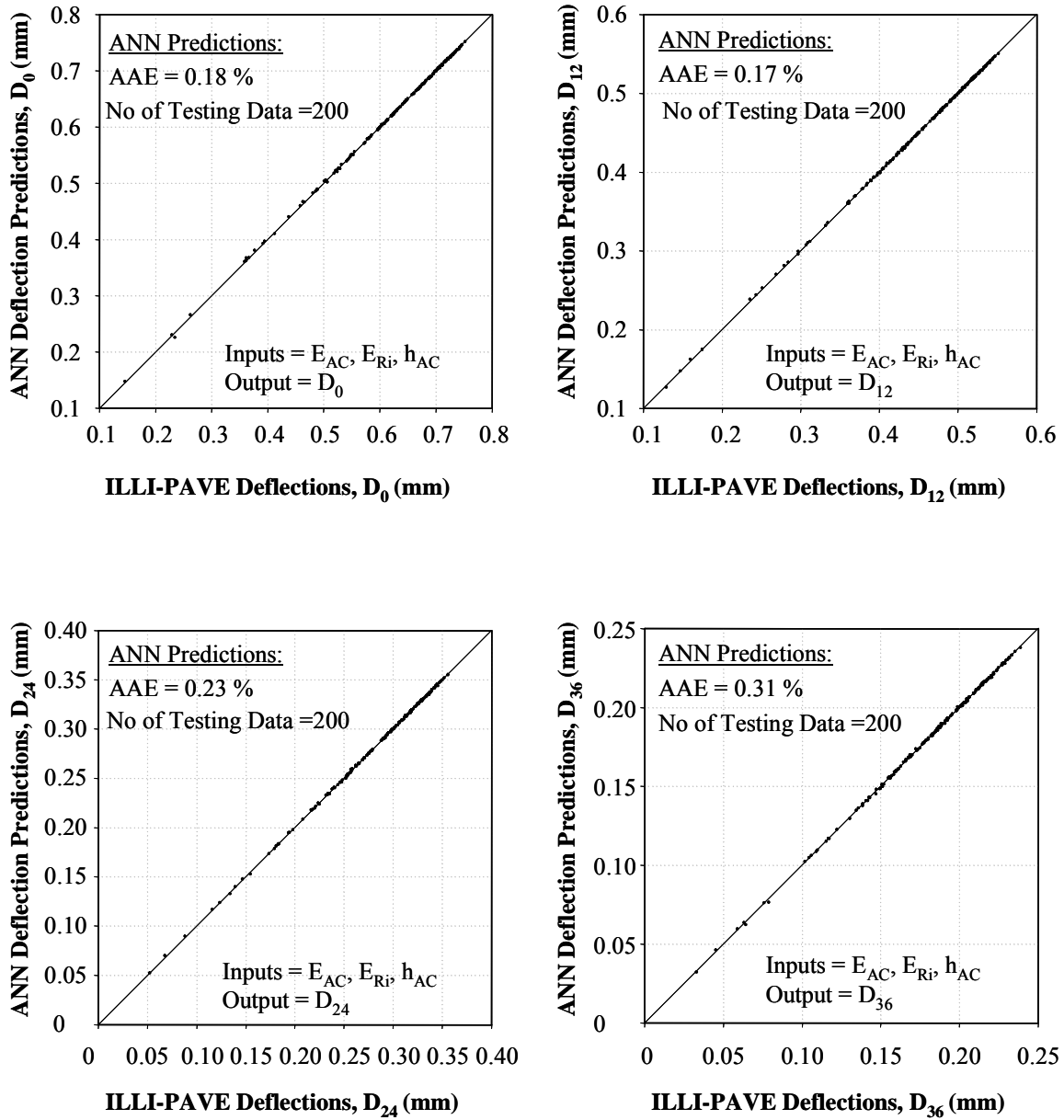


FIGURE 5 Forward Calculation Model 1 (FCM-1) for Predicting Pavement Surface Deflections

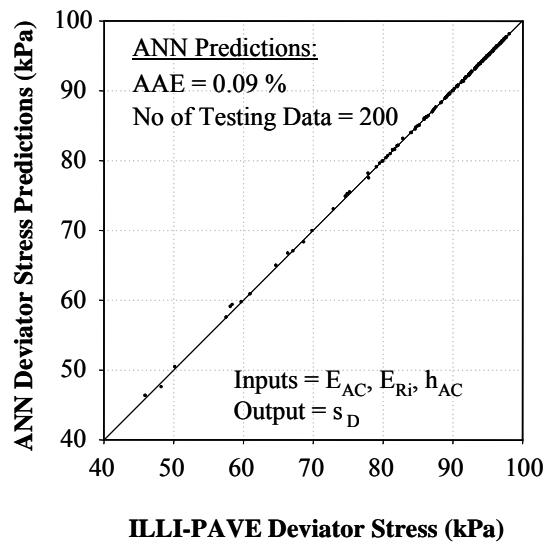
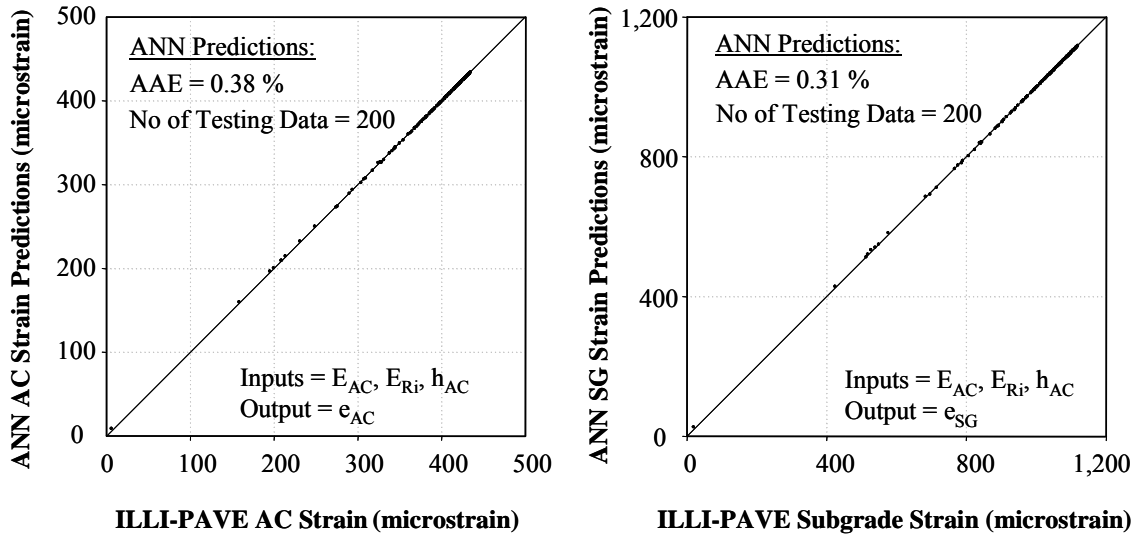
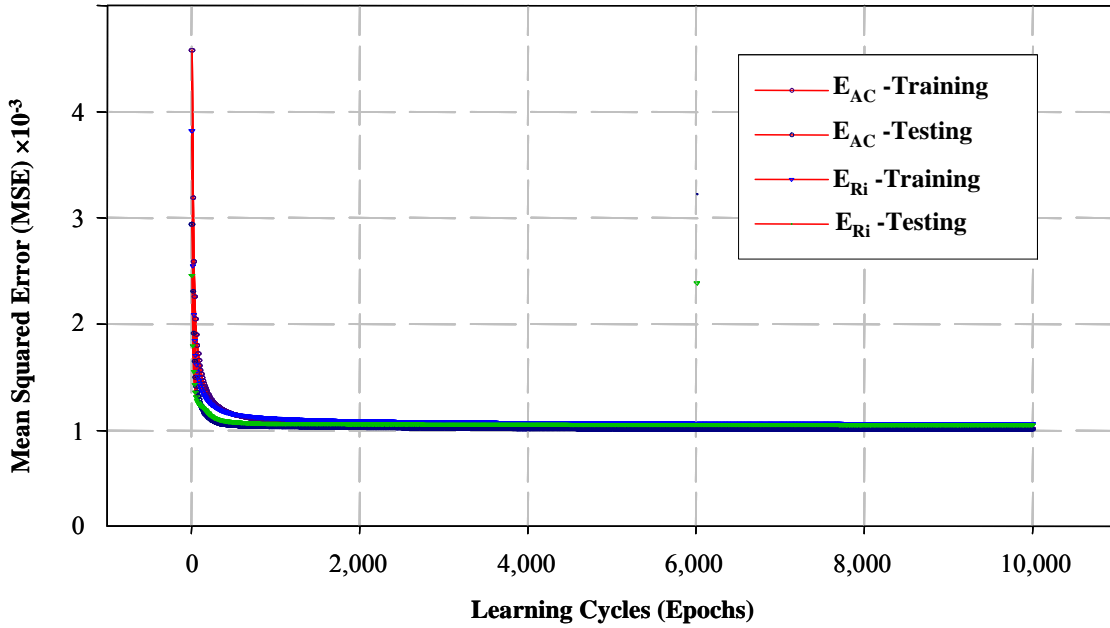
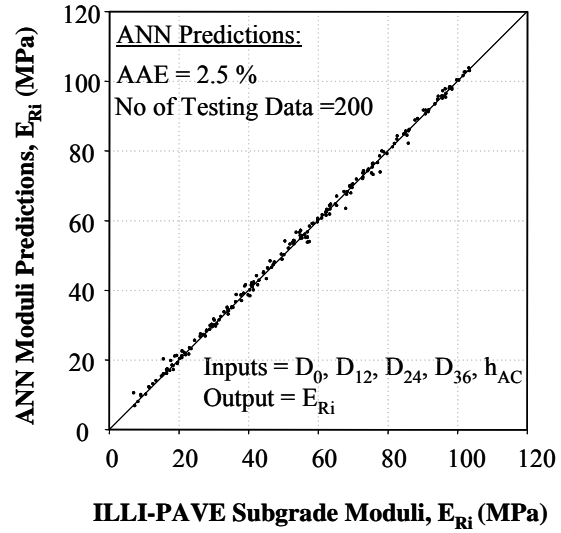
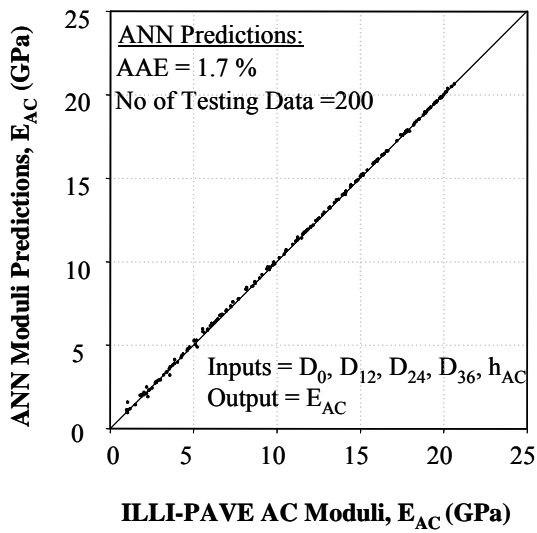


FIGURE 6 Forward Calculation Model 2 (FCM-2) for Predicting Critical Pavement Responses



(a)



(b)

FIGURE 7 (a) BCM-1 Training Progress Curve
 (b) Accuracy of the 5-60-60-2-10,000 Network for Predicting E_{AC} and E_{Ri}

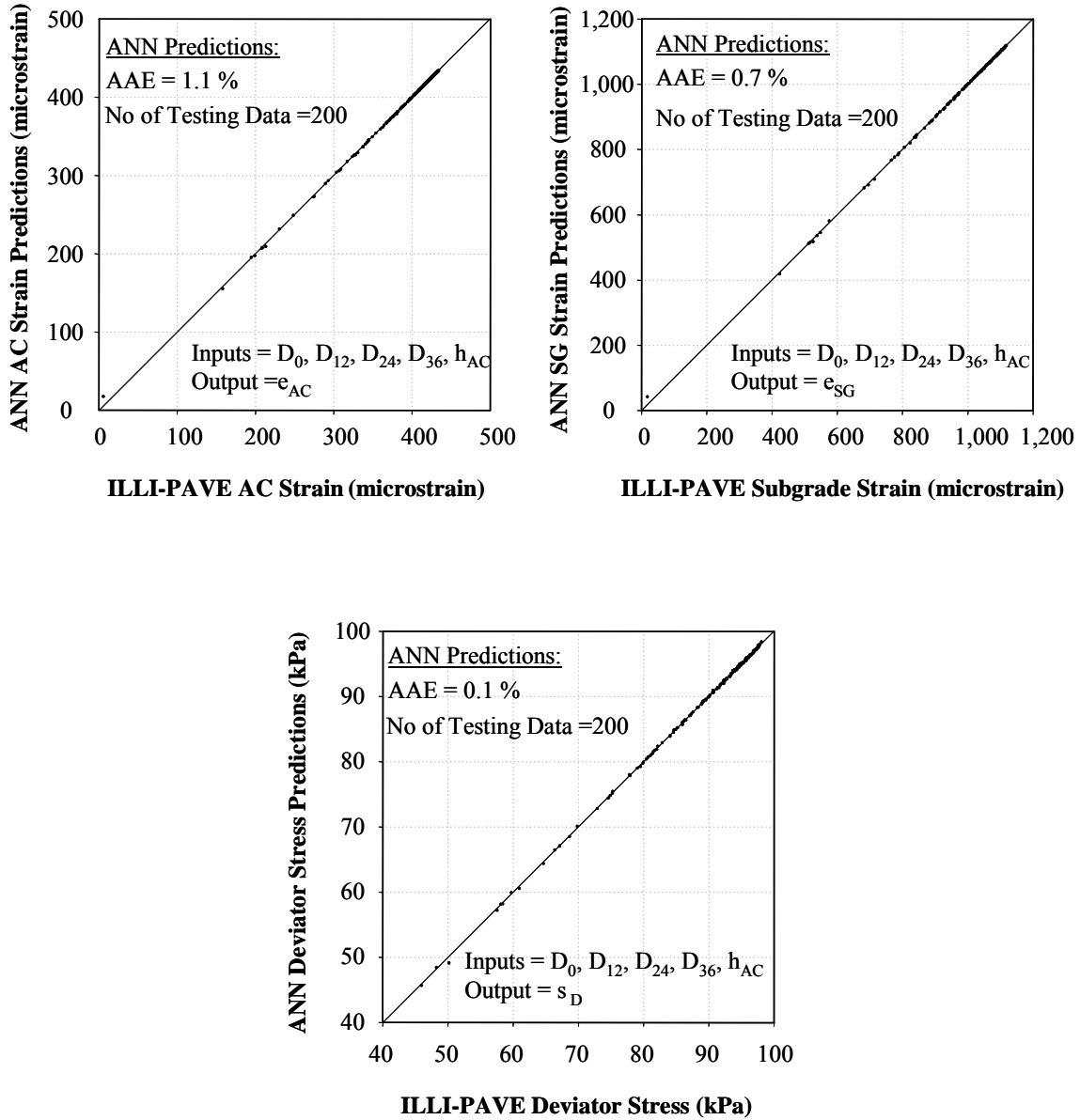


FIGURE 8 BCM-2 5-60-60-3-10,000 Network for the Prediction of ϵ_{AC} , ϵ_{SG} , and σ_D

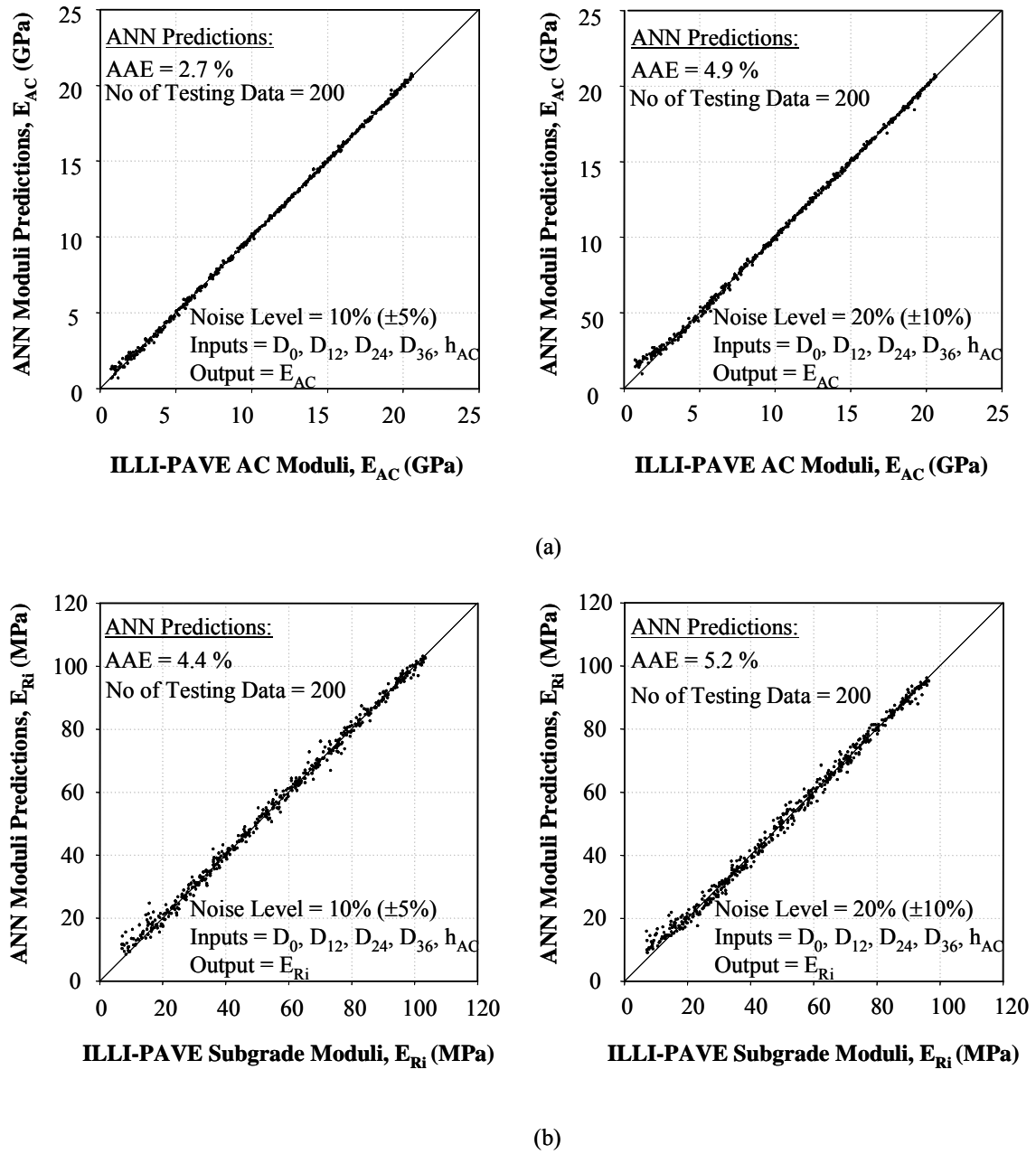


FIGURE 9 BCM-1 5-60-60-2-10,000 Network for the Predictions of E_{AC} (a) and E_{Ri} (b) with 10% and 20% Deflection Noise Levels

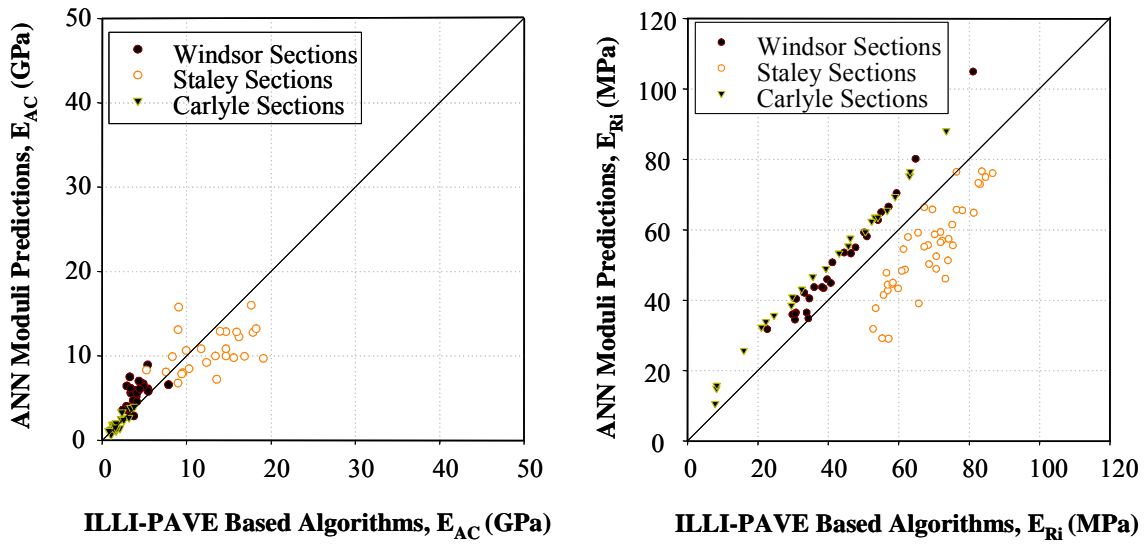


FIGURE 10 ANN Moduli Predictions Compared with the ILLI-PAVE-Based Algorithms Developed by Thompson [18]

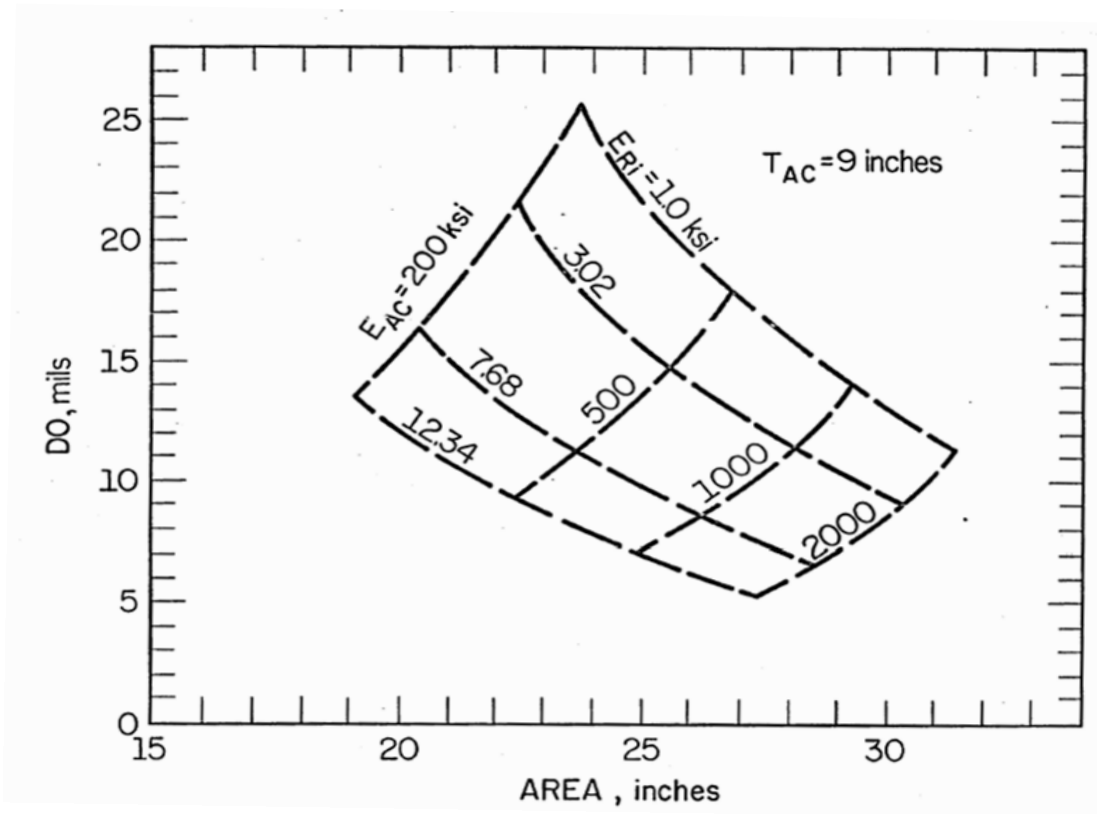


FIGURE 11 D₀-AREA Interpretation for Full-Depth Asphalt Concrete for 9 in. Thick AC Pavement [18]

TABLE 1 Pavement Geometry and Material Model Inputs for ILLI-PAVE 2000 Solutions

Material Type	Layer Thickness	Material Model	Layer Modulus Range	Poisson's Ratio
Asphalt Concrete	$h_{AC} = 152$ to 610 mm (6 to 24 in.)	Linear Elastic	$E_{AC} = 690$ to $20,700$ MPa (100 to 3,000 ksi)	$\nu = 0.35$
Fine- Grained Subgrade	$h_{SG} = 8,534$ to $8,992$ mm (336 to 354 in.) ($h_{SG} = 360$ in. - h_{AC})	Nonlinear Bilinear Model	$M_R = f(E_{Ri})$; $E_{Ri} = 6.9$ to 103.5 MPa (1 to 15 ksi) see FIGURE 1	$\nu = 0.45$