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Backcalculation of Layer Moduli for Jointed Plain Concrete Pavement Systems Using Artificial Neural Networks

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ABSTRACT

The objective of this study was to develop artificial neural network (ANN)-based backcalculation models for predicting the layer moduli of the jointed plain concrete pavements (JPCPs), i.e. the elastic modulus of Portland cement concrete (PCC) layer (E_{PCC}) and the coefficient of subgrade reaction (k_s) of the pavement foundation. The ANN-based models were trained to predict the moduli based on the falling weight deflectometer (FWD) deflection basin data and the thickness of the concrete pavement structure. The ISLAB2000 finite element program, extensively tested and validated for over 20 years, has been used as an advanced structural model for solving the responses of the rigid pavement systems and generating a large knowledge database. ANN-based backcalculation models trained with the results from the ISLAB2000 solutions have been found to be viable alternatives for rapid assessment (capable of analyzing 100,000 FWD deflection profiles in one second) of the rigid pavement systems. The trained ANN-based models were capable of predicting the concrete pavement parameters with very low average absolute error (AAE) values ($< 0.4\%$ for synthetic deflection basins). The ANN model predictions and closed-form solutions were compared using the actual FWD deflection basin data and the results are summarized in this paper. In addition, a sensitivity study was conducted to verify the significance of the layer thicknesses and the effect of bonding between the PCC and the base layer in the backcalculation procedure. The results of this study demonstrated that the developed ANN-based models can successfully predict the Young's modulus of the PCC layer and the coefficient of subgrade reaction values with high accuracy.

Key Words: Artificial Neural Networks, Falling Weight Deflectometer, Finite Element Analysis, Rigid Pavements, Pavement Layer Backcalculation, Nondestructive Testing and Evaluation

INTRODUCTION

Falling weight deflectometer (FWD) and heavy weight deflectometer (HWD) testing have become the main nondestructive testing (NDT) techniques to structurally evaluate the in-service pavements over the last twenty years. Falling weight deflectometer testing is often preferred over destructive testing methods because FWD testing is faster than destructive tests and do not entail the removal of pavement materials. In addition, the testing apparatus is easily transportable. Pavement properties are “backcalculated” from the observed dynamic response of the pavement surface to an impulse load (the falling weight). To evaluate the structural condition of in-service pavements and to characterize the layer properties as inputs into available numerical or analytical programs, backcalculation of pavement layer properties is a very useful tool. Most backcalculation procedures estimate pavement properties by matching measured and calculated pavement surface deflection basins.

There are many advantages to using FWD tests, in lieu of, or supplement traditional destructive tests for pavement structural evaluation. Most important, is the capability to quickly gather data at several locations while keeping a runway, taxiway, or apron operational during these 2-minute to 3-minute tests, provided the testing is performed in close coordination with the Air Traffic Control. Without FWD/HWD testing, structural data must be obtained from numerous cores, borings, and excavation pits on existing highway/airport pavements. This can be very disruptive to highway/airport operations. FWD tests are economical to perform and data can be collected at up to 250 locations per day. The FWD/HWD equipment measures pavement surface deflections from an applied dynamic load that simulates a moving wheel (*l*).

The elastic modulus of the slab, E_{PCC} , and the coefficient of subgrade reaction, k_s , are the backcalculated layer moduli parameters for the JPCP systems. Over the years, researchers have developed several different methodologies for backcalculation of concrete pavement layer moduli from FWD measurements, including the AREA method for rigid pavements (2-4), ILLI-BACK (5), graphical solution using ILLI-SLAB (6), use of regression analysis to solve AREA method for rigid pavements (7,8), use of best fit algorithm to find radius of relative stiffness (ℓ), (8,9), and many others. The primary focus of this study is the estimation of the rigid pavement parameters with high accuracy using ANNs, particularly the determination of the elastic modulus of the slab and the coefficient of subgrade reaction of the pavement foundation that are used in the analysis and design of the rigid pavements. FWD deflections and PCC thickness of the test section are the only information needed for the backcalculation of the rigid pavement parameters with developed ANN-based models. There is no need for the provision of seed moduli in this approach. The use of the ANN models also results in a drastic reduction in computation time compared to other methodologies.

FINITE ELEMENT PROGRAMS FOR RIGID PAVEMENTS

Today, a variety of finite element (FE) programs are available for the analysis and design of pavement systems. The two main categories of FE programs are those: (1) programs specifically designed for the analysis of pavement systems, and (2) general-purpose programs. Finite element programs such as ABAQUS, ANSYS, and DYNA3D are powerful general-purpose programs with three-dimensional nonlinear dynamic analysis capabilities. In several research studies, these programs have successfully been used for pavement analysis. A number of FE models built using

these programs have been reported in the literature (10-12). On the other hand, considerable computational resources and time needed for analyzing a structural system are among the limitations of the general-purpose FE programs.

There are also FE-based programs developed specifically for analysis of concrete pavement systems such as ISLAB2000 (13-15), DIPLOMAT (16), KENSLABS (17), WESLIQID (18), J-SLAB (19), FEACONS-IV (20), KOLA (21), and EverFE (22). Most of these programs can analyze multi-wheel loading of one- or two-layered medium thick plates resting on a Winkler foundation or elastic solid (ISLAB2000, KENSLABS, WESLIQID). EverFE can analyze multi-layered pavement systems using a 3D-continuum brick element for the Portland cement concrete (PCC) and base layers. ISLAB2000 contains many advanced features that distinguish it from other pavement programs that are based on the plate theory.

In addition to the FE programs, Westergaard (23) solutions (plate theory) for PCC pavements are also used to analyze the rigid pavements. ANN trainings are also used to interpret results from databases of deflection profiles to estimate pavement properties (24-26). Although there are different FE programs and other approaches to analyze the rigid pavements, all methods do not produce exactly the same results. In order to better understand the results produced by different programs, a sensitivity analysis was performed as part of this study.

Comparison of Finite Element Models and Closed-Form Solutions

A sensitivity study was performed to analyze the differences in the slab-center deflections (D_0 , the maximum FWD deflection) obtained from ISLAB2000, DIPLOMAT, KENSLABS and Westergaard solutions. ISLAB2000 is a FE modeling program designed specifically for analyzing rigid pavements. In large part, it is an extension and improvement of the ILLI-SLAB (6) and ILSL2 (14) programs. ISLAB2000 is a significant improvement over its predecessors for the analysis of rigid pavement systems, enabling users to analyze a wide range of problems.

ISLAB2000 allows the user to define an “unlimited” number of nodes, pavement layers, and wheel loads. It also includes an improved void analysis model. DIPLOMAT was developed by Khazanovich and Ioannides (16), which is an extension of elastic layer and plate theories. Several programs have been developed based on Burmister elastic layer solutions, but only DIPLOMAT can model pavement layers as plates, springs and/or elastic layers together. On the other hand, one disadvantage of DIPLOMAT and other elastic layer programs (ELPs) is that joints cannot be modeled because layers are assumed infinite in the horizontal direction. The KENSLABS computer program is based on the FE method, in which slabs are divided into rectangular FE with a large number of nodes. KENSLABS can be applied to a maximum of 6 slabs, 7 joints, and 420 nodes. Both wheel loads and subgrade reactions are applied to the slab as vertical concentrated forces at the nodes.

In this study, plate theory was used in the analyses and the pavement foundation is assumed as dense-liquid foundation (as Winkler-spring method). Different configurations of E_{PCC} , h_{PCC} , and k_s were defined and the D_0 deflections obtained from ISLAB2000, DIPLOMAT, and KENSLABS FE programs and Westergaard solutions were compared with each other (see Figure 1). The deflection profiles obtained from ISLAB2000, DIPLOMAT, and KENSLABS FE models for two pavement configurations were also presented in Figure 2.

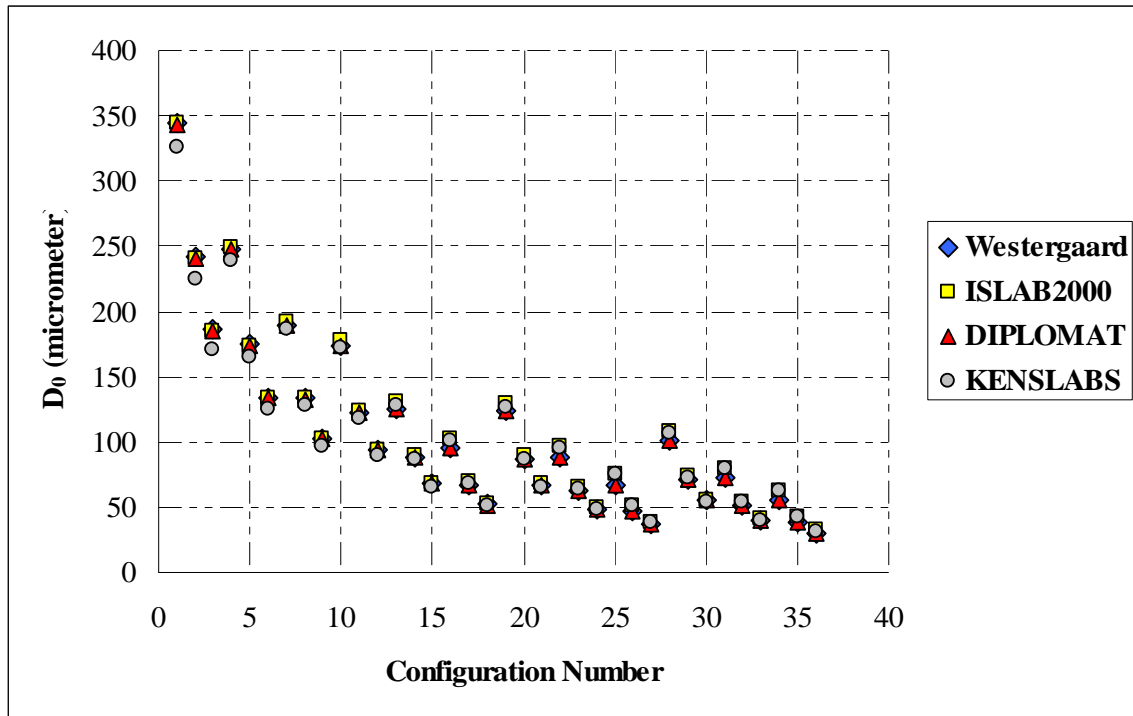


FIGURE 1 Comparison of ISLAB2000, DIPLOMAT, and KENSLAB finite element model solutions with Westergaard theoretical solutions.

As can be seen from Figures 1 and 2, a good match was obtained for results from different models. Finally, a solution database using the ISLAB2000 FE model was created since the ISLAB2000 is convenient due to the ease of modeling and flexibility in the analysis compared to other methods. ISLAB2000 can also analyze partially bonded layers, the effects of nonlinear temperature distribution throughout the constructed layers, the mismatched joints and cracks and the effect of voids under the slab. On the other hand, there might be various reasons of the observed differences in the deflection profiles obtained from different methods. These reasons can be listed as follows.

- ISLAB2000 and KENSLABS use finite slabs in the analysis (slab sizes, joints, and load transfer efficiencies must be identified in the programs) but DIPLOMAT and Westergaard solutions do not take into account the slab size, joints and load transfer efficiencies.
- ISLAB2000 and KENSLABS use a rectangular or square loading area. On the other hand, DIPLOMAT and Westergaard solutions consider circular loading area.

A general view of the ISLAB2000 FE solution database used in this study is shown in Figure 3.

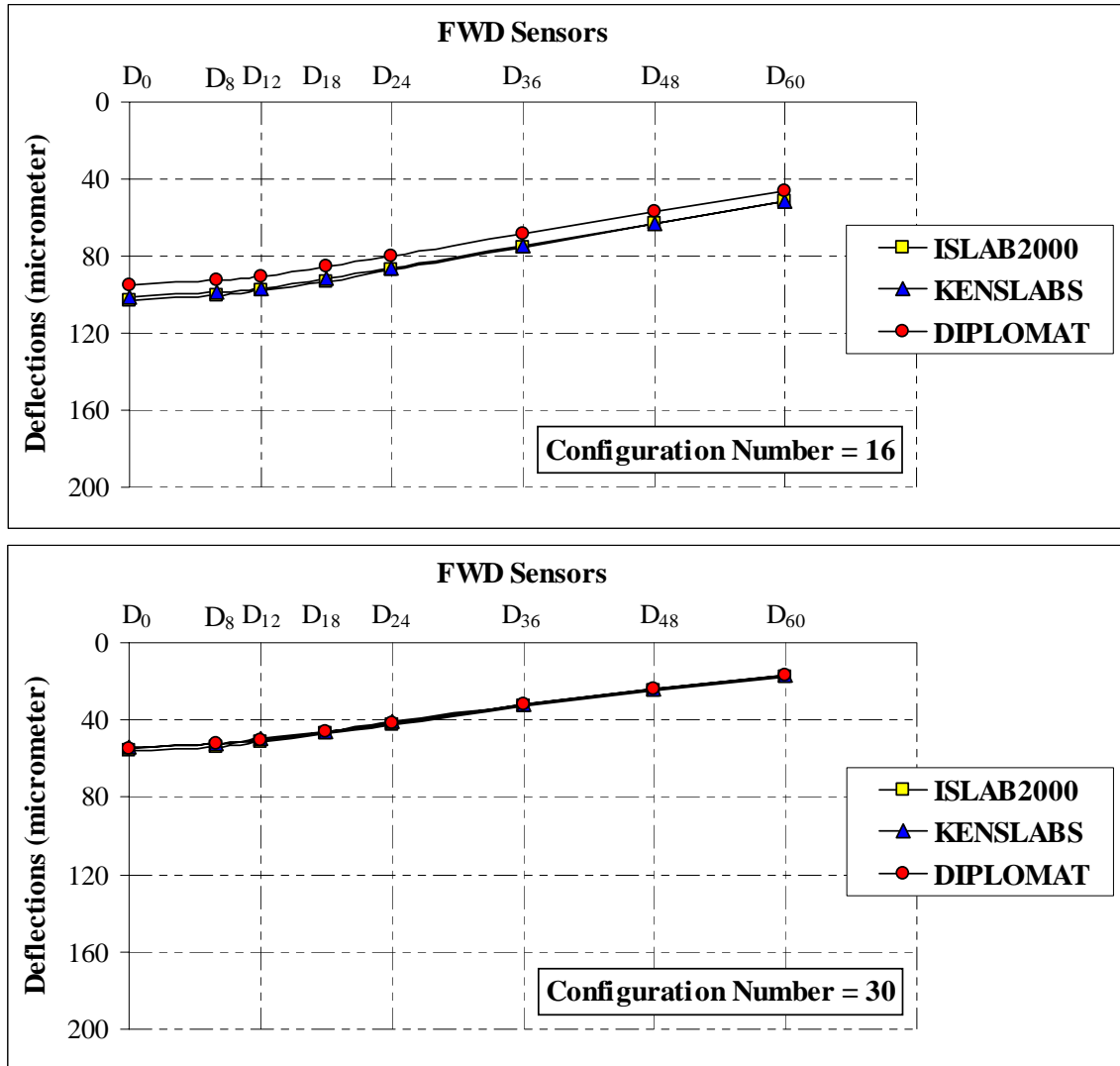


FIGURE 2 Comparison of ISLAB2000, DIPLOMAT, and KENSLAB finite element model solutions for different pavement configurations.

GENERATING ISLAB2000 FINITE ELEMENT SOLUTION DATABASE

In order to train the ANN models, a total of 51,714 ISLAB2000 runs were generated by modeling slab-on-grade concrete pavement systems. A single slab layer resting on a Winkler foundation was analyzed in all cases. Concrete pavements analyzed in this study were represented by a six-slab assembly, each slab having dimensions of 6.1 m by 6.1 m (20 ft by 20 ft) (see Figure 4).

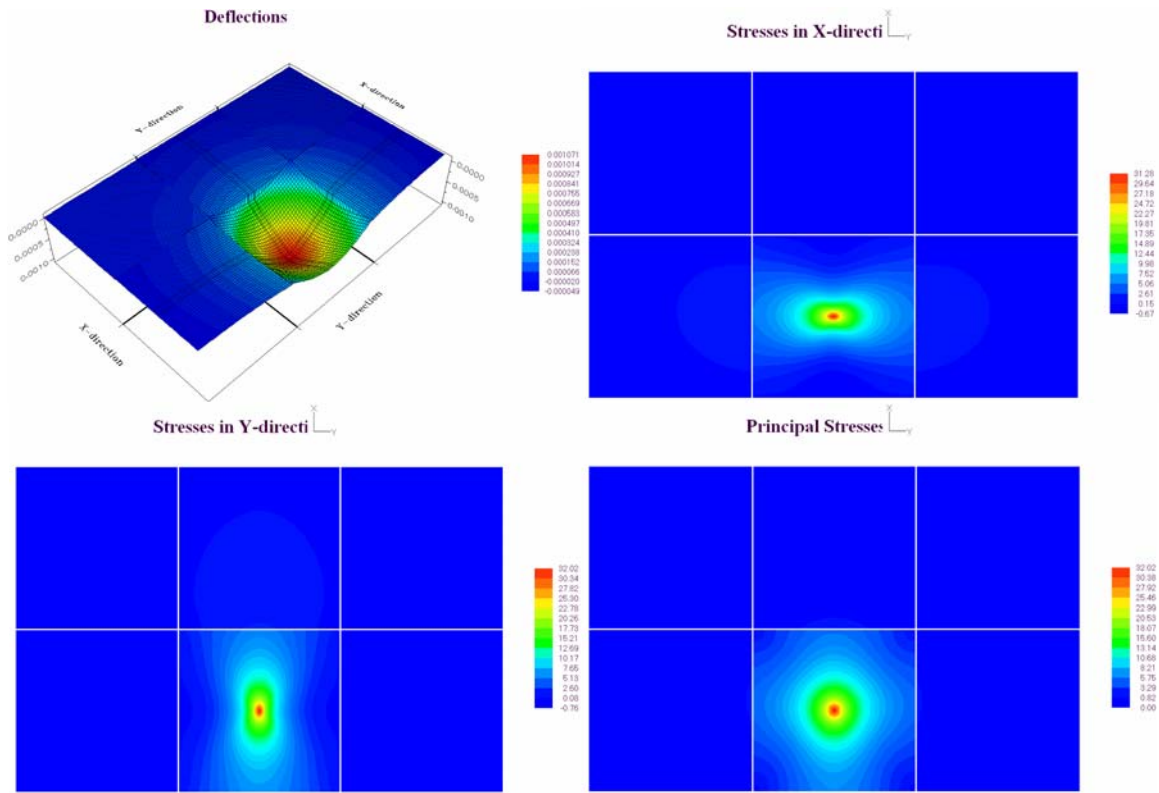


FIGURE 3 A general view of the deflections and stresses at the bottom of the PCC slab under 9-kip loading in six-slab assembly.

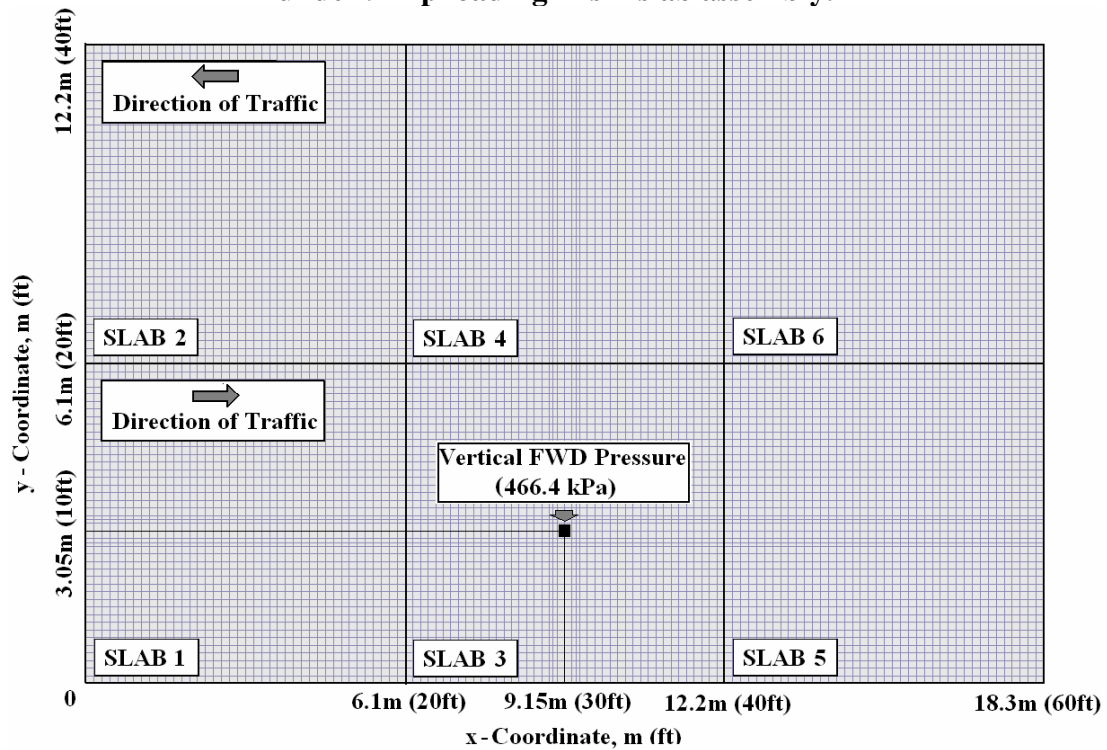


FIGURE 4 ISLAB2000 finite element model meshing for the six-slab JPCP assembly.

To maintain the same level of accuracy in the results from all analyses, a standard ISLAB2000 finite element mesh was constructed for the slab. This mesh consisted of 10,004 elements with 10,209 nodes. The ISLAB2000 solutions database was generated by varying the elastic modulus of PCC slab (E_{PCC}), coefficient of subgrade reaction (k_s), and thickness of PCC layer (h_{PCC}) over a range of values representative of realistic variations in the field. The ranges used in the analyses are shown in Table 1. The Poisson's ratio (μ), the slab width (W), the slab length (L), PCC unit weight (γ), and coefficient of thermal expansion (α) were set equal to 0.15, 6.1 m (20 ft), 6.1 m (20 ft), 2408.15 kg/m³ (0.087 lb/in³), 9.9×10^{-6} 1/°C (5.5×10^{-6} 1/°F), respectively.

TABLE 1 Ranges of the input parameters used in the ISLAB2000 database generation

Pavement System Inputs	Min. Value	Max. Value
E_{PCC} , GPa (ksi)	6.90 (1,000)	103.50 (15,000)
k_s , kPa/mm (psi/in)	13.57 (50)	271.30 (1,000)
h_{PCC} , cm (in)	15.24 (6)	63.50 (25)

The total number of the ISLAB2000 runs conducted in this study was 51,714. However, some of the deflections obtained from ISLAB2000 (especially D_{48} , D_{60} and far outer deflections) had negative values (upward) due to the very low E_{PCC} , h_{PCC} , and k_s combinations. Therefore, the FE runs with negative deflections were excluded from the database used for the ANN trainings. The number of patterns included in the ANN trainings were 51,539 and 41,026 for k_s and E_{PCC} predictions, respectively. For each training, the ISLAB2000 solution database was first portioned to create a training set (TRN Set) of 49,539 (97.5 %, for k_s) and 39,026 (95 % for E_{PCC}) and an independent testing set (TST Set) of 2,000 patterns to check the prediction performance of the trained ANN models. Backpropagation type ANN architectures with two hidden layers were used for the ANN models trained in this study (25,26).

Subgrade Soil Characterization

The dense liquid (DL) model, proposed by Winkler (27), was used to characterize the subgrade behavior in this study. Accurate modeling of subgrade support for pavement systems is not a simple task since many soil types exhibit non-linear, stress dependent elasto-plastic behavior especially under the moving heavy wheel loads. Nevertheless, experience in rigid pavements analysis and design has shown that subgrade layer may be modeled as linear elastic because of the lower levels of vertical stresses acting on rigid pavement foundations.

A plate on a dense liquid foundation is the most widely adopted mechanistic idealization for analysis of concrete pavements (28). Dense liquid foundation is implemented in several FE models, such as ISLAB2000, DIPLOMAT, KENSLABS, WESLIQID, J-SLAB, and FEACONS III (29). Consideration of the critical load transfer phenomena, occurring at the PCC slab joints, and the concomitant development of major distress types, such as faulting, pumping and corner breaking are the significant advantages of this approach. The DL foundation is the simplest foundation model and requires only one parameter, the coefficient of subgrade reaction, k_s , which is the proportionality constant between the applied pressure and the load plate deflection. Subgrade deformations are local in character, that is, they develop only beneath the load plate.

Furthermore, their behavior is considered linear-elastic and deformations are recoverable upon removal of load (28).

ARTIFICIAL NEURAL NETWORKS (ANNs) AS PAVEMENT ANALYSIS TOOLS

There are several different types of ANN such as backpropagation neural networks (BPNN), radial basis function networks (RBFNN), probabilistic neural networks (PNN), and generalized regression neural networks (GRNN), to name a few. Computing abilities of neural networks have been proven in the fields of prediction and estimation, pattern recognition, and optimization (30-34). The best-known example of a neural network training algorithm is backpropagation (35-38) which is based on a gradient-descent optimization technique. The backpropagation neural networks are described in many sources (34,39-42). A comprehensive description of ANNs is beyond the scope of this paper. The adoption and use of ANN modeling techniques in the recently released Mechanistic-Empirical Pavement Design Guide (NCHRP project 1-37A: Development of the 2002 Guide for the Design of New and Rehabilitated Pavement Structures: Phase II) has especially placed the emphasis on the successful use of neural networks in geomechanical and pavement systems.

ANN-BASED PAVEMENT LAYER BACKCALCULATION MODELS

In this study, two groups of ANN-based backcalculation models were developed, which are BCM- k_s models and BCM- E_{PCC} models. FWD deflection readings [D_0 (0-mm), D_8 (203-mm), D_{12} (304-mm), D_{18} (457-mm), D_{24} (610-mm), D_{36} (914-mm), D_{48} (1,219-mm), and D_{60} (1,524-mm)] and PCC layer thickness (h_{PCC}) were used as input parameters in the developed ANN backcalculation models. Separate ANN architectures were used for the backcalculation of elastic modulus of the slab and the coefficient of subgrade reaction. Four-, six-, seven-, and eight-deflection ANN models were developed for backcalculating the k_s and E_{PCC} values (see Table 2).

TABLE 2 ANN architectures and average absolute error values for the ANN-based backcalculation models

ANN Models	Input Parameters	ANN Architecture	AAE (%)
BCM- k_s -(4)	$D_0, D_{12}, D_{24}, D_{36}$	4-60-60-1	0.28
BCM- k_s -(6)	$D_0, D_{12}, D_{24}, D_{36}, D_{48}, D_{60}$	6-60-60-1	0.20
BCM- k_s -(7)	$D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{60}$	7-60-60-1	0.19
BCM- k_s -(8)	$D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60}$	8-60-60-1	0.22
BCM- E_{PCC} -(4)	$D_0, D_{12}, D_{24}, D_{36} + h_{PCC}$	5-60-60-1	0.34
BCM- E_{PCC} -(6)	$D_0, D_{12}, D_{24}, D_{36}, D_{48}, D_{60} + h_{PCC}$	7-60-60-1	0.32
BCM- E_{PCC} -(7)	$D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{60} + h_{PCC}$	8-60-60-1	0.29
BCM- E_{PCC} -(8)	$D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60} + h_{PCC}$	9-60-60-1	0.30

Backcalculation Models

A network with two hidden layers was exclusively chosen for all models trained in this study. Satisfactory results were obtained in the previous studies with these types of networks due to

their ability to better facilitate the nonlinear functional mapping (43,44). ANN architectures, input parameters, output variables, and AAE values of all developed models are tabulated in Table 2. The comparison of the ISLAB2000 solutions and ANN predictions for k_s and E_{PCC} are shown in Figures 5 and 6, respectively. Also, Figure 7 shows the training and testing MSE progress curves for the BCM- k_s -(6) and BCM- E_{PCC} -(4) models.

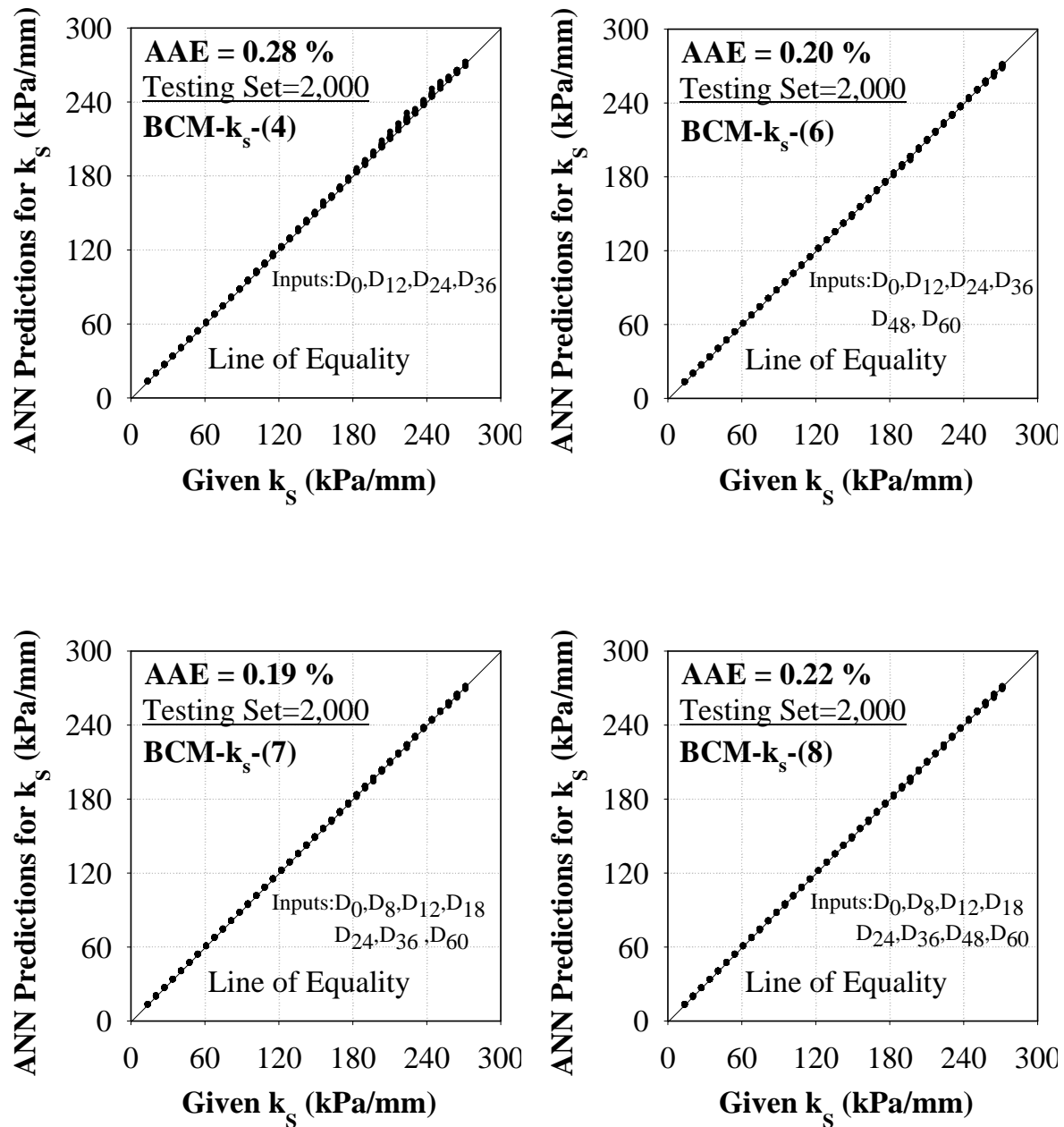


FIGURE 5 Prediction performance of ANN-based models for backcalculating the coefficient of subgrade reaction, k_s .

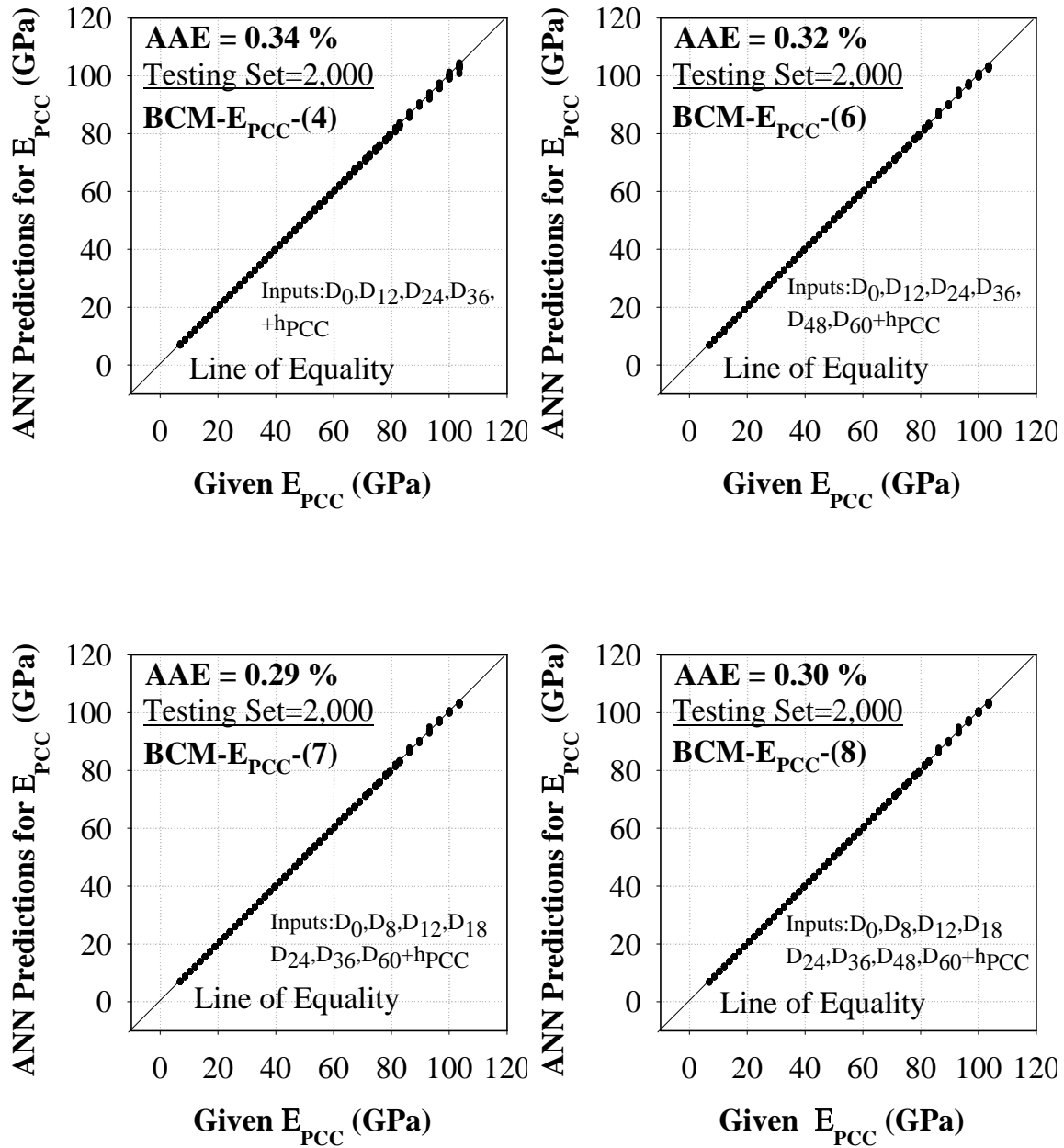
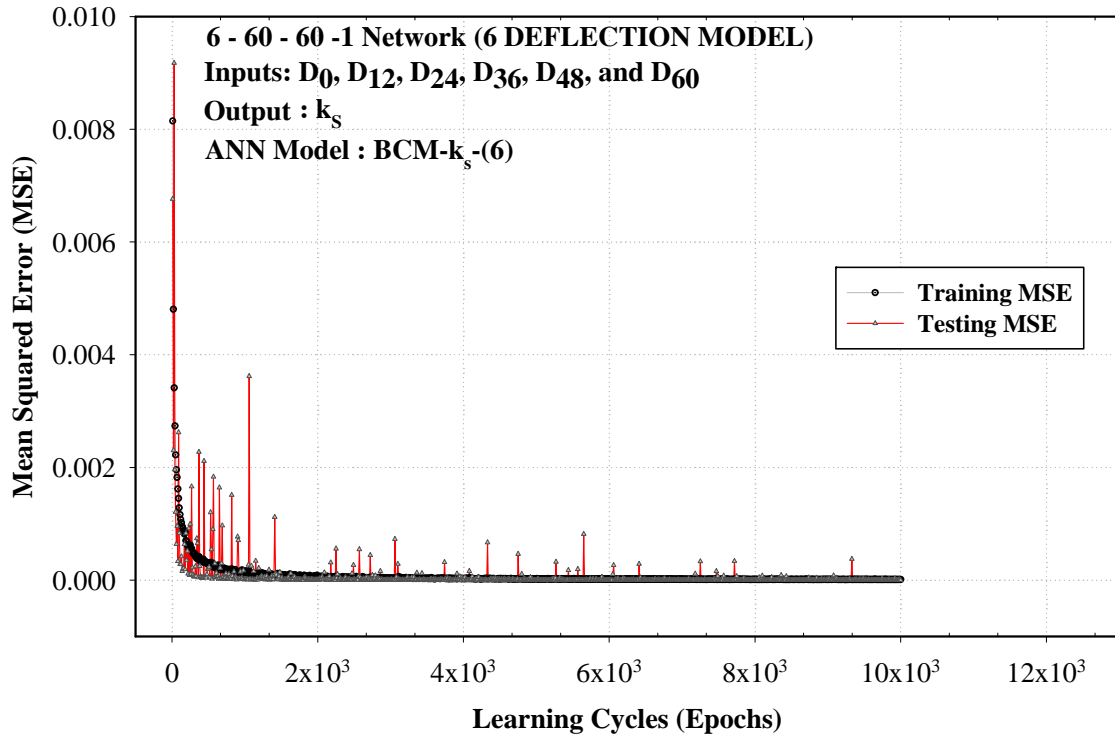
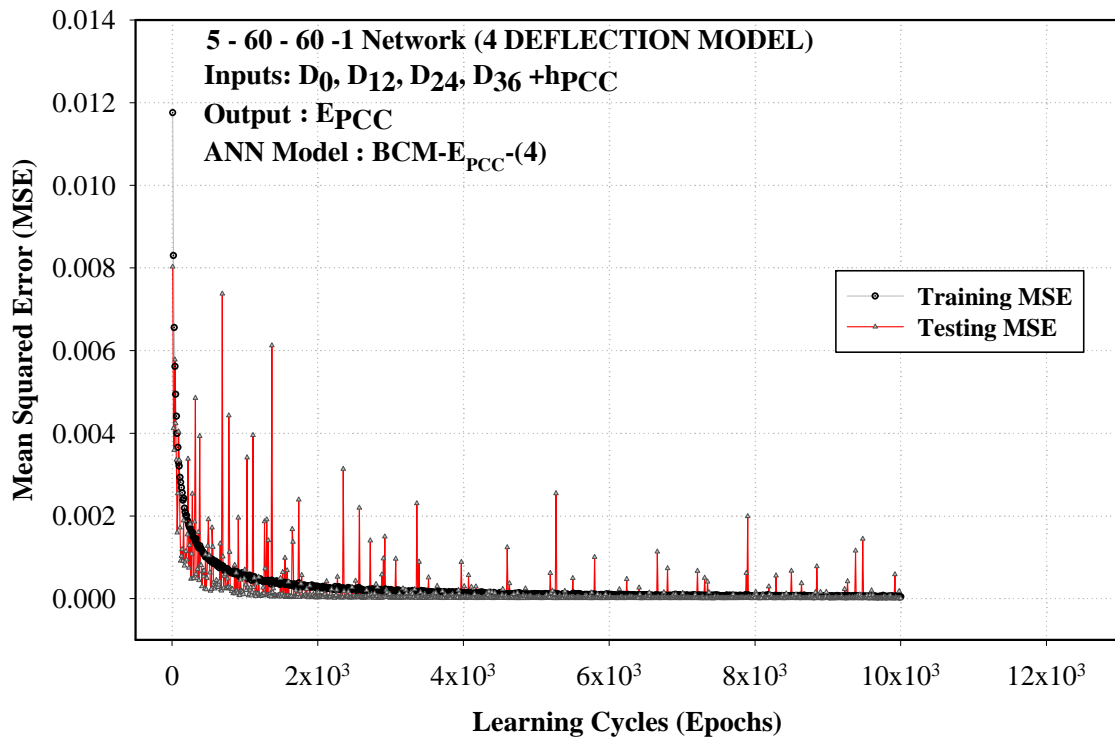


FIGURE 6 Prediction performances of ANN-based models for backcalculating the PCC layer modulus, E_{PCC} .



(a)



(b)

FIGURE 7 Training progress curves for: (a) BCM- k_s -(6) model, and (b) BCM-E_{PCC}-(4) model.

THE SIGNIFICANCE OF LAYER BONDING AND THICKNESS IN THE PAVEMENT LAYER BACKCALCULATION

Two of the important issues in the backcalculation of the rigid pavement parameters are the degree of bonding between layers and thickness of the PCC and base layers. To simplify the ANN-based backcalculation methodology developed in this study, only one thickness value (effective PCC thickness) was considered in the analysis. The effective thickness of the pavement structure is directly related to the bonding conditions between the PCC layer and the base layer. Since it is difficult to construct a long pavement section with a uniform thickness value, during the backcalculation of the pavement parameters, it is assumed that pavement thickness is uniform for a given section and it's the value taken from the project files. To determine the effective thickness of a two-layer pavement section for bonded, unbonded, and partially bonded cases, the equations given below are considered (45).

Effective thickness for fully bonded PCC layers was computed using the following equations:

$$h_{e-b} = \left\{ h_1^3 + \frac{E_2}{E_1} h_2^3 + 12 \left[\left(x_{na} - \frac{h_1}{2} \right)^2 h_1 + \frac{E_2}{E_1} \left(h_1 - x_{na} + \frac{h_2}{2} \right)^2 h_2 \right] \right\}^{1/3} \quad (1)$$

$$x_{na} = \frac{E_1 h_1 \frac{h_1}{2} + E_2 h_2 \left(h_1 + \frac{h_2}{2} \right)}{E_1 h_1 + E_2 h_2} \quad (2)$$

Effective thickness for unbonded PCC layers was computed using the following equations:

$$h_{e-u} = \left(h_1^3 + \frac{E_2}{E_1} h_2^3 \right)^{1/3} \quad (3)$$

Effective thickness for partially bonded PCC layers was computed using the following equations:

$$h_{e-p} = (1-x)h_{e-u} + (x)h_{e-b} \quad (4)$$

$$x = \frac{h_{e-p} - h_{e-u}}{h_{e-b} - h_{e-u}} \quad (5)$$

where as;

- h_{e-b} = Effective thickness of the fully bonded PCC layers
- h_{e-u} = Effective thickness of the unbonded PCC layers
- h_{e-p} = Effective thickness of the partially bonded PCC layers
- E_1 or E_2 = Elastic modulus for layer 1 or 2
- h_1 or h_2 = Thickness for layer 1 or 2

- x_{na} = Neutral axis distance from top of layer
- x = Degree of bonding which ranges between 0 and 1

The effect of the layer thickness in the E_{PCC} predictions

The predicted layer moduli are very sensitive to the pavement layer thickness. Even a small change in the assumed PCC layer thickness causes considerable differences in the backcalculated elastic moduli of the PCC layer. To demonstrate the effect of the PCC thickness on the backcalculated E_{PCC} values, FWD data collected from the FAA’s National Airport Pavement Test Facility (NAPTF) were used (see Figure 8).

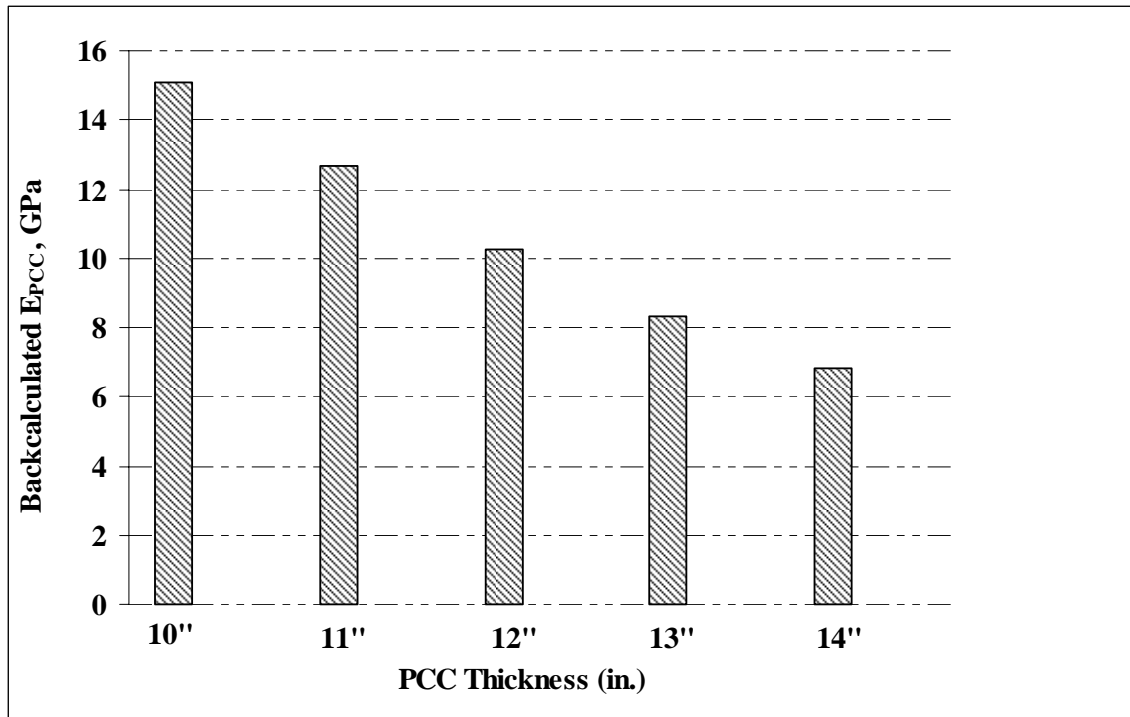


FIGURE 8 Effect of layer thickness on E_{PCC} backcalculation.

The effect of pavement layer bonding in the E_{PCC} predictions

The LRS (rigid pavement with stabilized base over low-strength subgrade) data was used to investigate the sensitivity of the thickness and the degree of the bonding between the layers. The thickness and elastic modulus values for the LRS test section are assumed as follows: $E_{PCC} = 34.5$ GPa (5,000,000 psi), $E_{base} = 6.9$ GPa (1,000,000 psi), $h_{PCC} = 28$ cm (11 in.), and $h_{base} = 15.6$ cm (6 1/8 in.). The effective thickness values were calculated as 28.2 cm (11.1 in.), 29.7 cm (11.7 in.), 31.0 cm (12.2 in.), 32.3 cm (12.7 in.), and 33.8 cm (13.3 in.) for the unbonded, 25% bonded, 50% bonded, 75% bonded, and fully bonded cases using the equations given above. The variation of the backcalculated E_{PCC} values for the LRS section is presented in Figure 9.

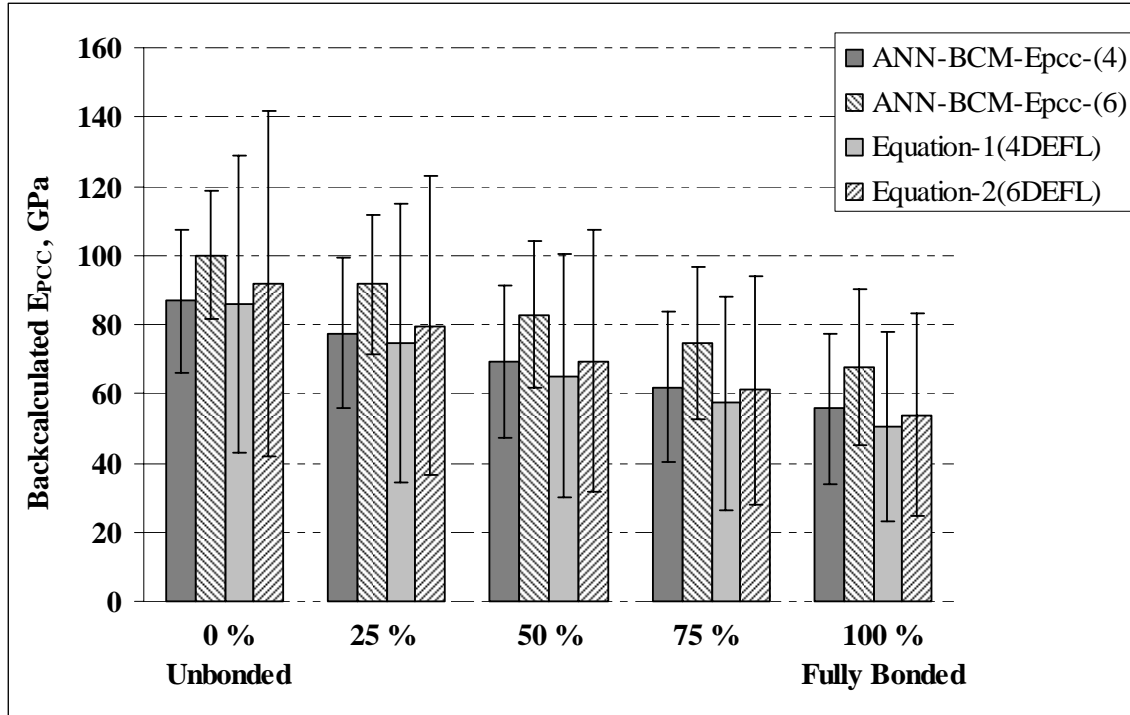


FIGURE 9 Effect of degree of layer bonding on Epcc backcalculation.

As seen in Figure 9, degree of layer bonding resulting in a 2.5 cm (1 in.) change in the effective thickness of the pavement system may change the backcalculated Epcc value 17 GPa (2.5 x10⁶ psi) with the assumed PCC and base layer moduli values. Therefore, results from this sensitivity analysis show the significance of the degree of bonding and pavement effective pavement thickness in the Epcc backcalculation procedure. The closed-form equations used in this sensitivity analysis were obtained from a statistical study with the ISLAB2000 solution database used in this paper. There is a unique relationship between AREA and radius of relative stiffness. ℓ (radius of relative stiffness) can be calculated from the AREA- ℓ equations. AREA value was calculated from 4 deflections ($D_0, D_{12}, D_{24},$ and D_{36}) and 6 deflections ($D_0, D_{12}, D_{24}, D_{36}, D_{48},$ and D_{60}) as shown in Equations 6 and 7 below. Load (P), radius of load plate (a), and Poisson's ratio (μ) were set to 40 kN (9-kip), 150 mm (5.9 in.) and 0.15, respectively. The equations used in the numerical backcalculation of the rigid pavement parameters are summarized below:

$$AREA_4(in.) = 6 * \left[1 + 2 \left(\frac{D_{12}}{D_0} \right) + 2 \left(\frac{D_{24}}{D_0} \right) + \left(\frac{D_{36}}{D_0} \right) \right] \quad (6)$$

$$AREA_6(in.) = 6 * \left[1 + 2 \left(\frac{D_{12}}{D_0} \right) + 2 \left(\frac{D_{24}}{D_0} \right) + 2 \left(\frac{D_{36}}{D_0} \right) + 2 \left(\frac{D_{48}}{D_0} \right) + \left(\frac{D_{60}}{D_0} \right) \right] \quad (7)$$

$$\ell_4(in.) = (-128.9885) + (5.4081797 * AREA_4) + (1.022406 * (AREA_4 - 30.8637)^2) + (0.1919404 * (AREA_4 - 30.8637)^3) + (0.0145737 * (AREA_4 - 30.8637)^4) \quad (8)$$

$$\ell_6(\text{in.}) = (-49.15008) + (1.9800955 * \text{AREA}_6) + (0.1146559 * (\text{AREA}_6 - 44.3008)^2) + (0.0075314 * (\text{AREA}_6 - 44.3008)^3) + (0.0002145 * (\text{AREA}_6 - 44.3008)^4) \quad (9)$$

$$k = \left(\frac{P}{8D_0 \ell_i^2} \right) \left\{ 1 + \left(\frac{1}{2\pi} \right) \left[\ln \left(\frac{a}{2\ell_i} \right) - 0.673 \right] \left(\frac{a}{\ell_i} \right)^2 \right\} \quad (10)$$

$$E_{PCC} = \left(\frac{12\ell_i^4 k (1 - \mu^2)}{h_{PCC}^3} \right) \quad (11)$$

VALIDATION OF THE ANN-BASED MODELS

Comparison of the ANN Models with Closed Form Equations

In order to validate the developed ANN-based backcalculation models, ANN model backcalculation results were compared with the closed-form equation results using the FWD/HWD test data obtained from the NAPTF. The FWD/HWD deflection profiles obtained from the NAPTF's LRS test sections are depicted in Figure 10.

All FWD/HWD test results were normalized to 40 kN (9-kip) in order to compare the results. The ANN BCM- k_s -(6) model predictions and closed-form equation solutions (Eqs. 7, 9, 10, and 11) are presented in Figure 11 for backcalculating the k_s using the NAPTF-LRS FWD data. In addition, ANN BCM- E_{PCC} -(4) model predictions and closed-form equation solutions (Eqs. 6, 8, 10, and 11) were compared and results are presented in Figure 12 for backcalculating the E_{PCC} value using the same FWD data. Please note that the layers were assumed as fully bonded in this analysis. As can be seen from the comparison of ANN models and closed-form equation predictions, the standard deviations for the ANN-based predictions are lower than the ones for closed-form equations. In addition, it can be concluded that the scatter of the predictions is strongly dependent on the dates due to the repeated trafficking that the FWD/HWD deflection tests were conducted (see Figure 10). Higher scattering in E_{PCC} predictions can be explained with E_{PCC} being dependent on the PCC layer thickness and the degree of bonding between the PCC and the Econcrete base layers.

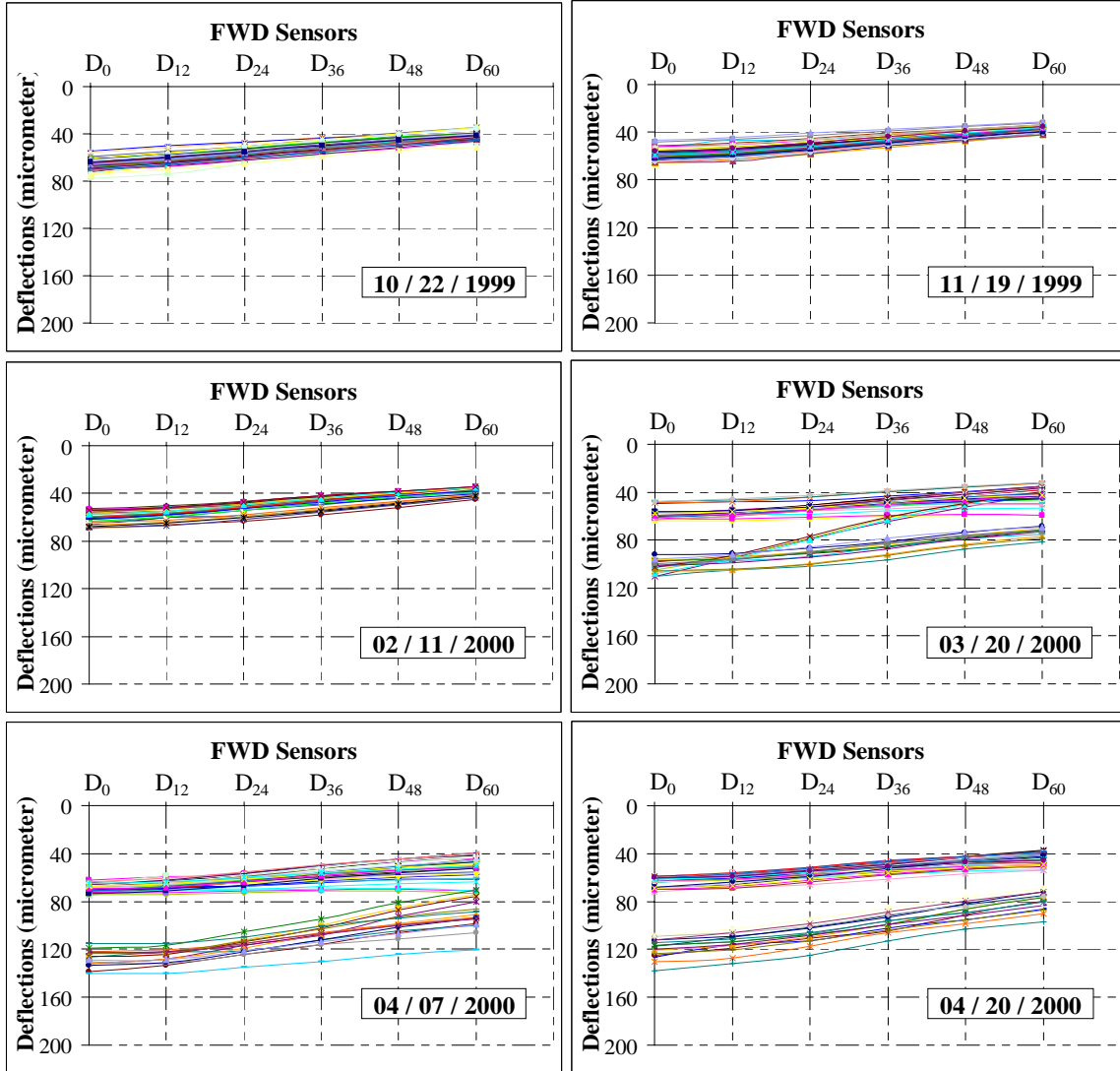


FIGURE 10 FWD/HWD deflection basins normalized to 40 kN load level for NAPTF-LRS section.

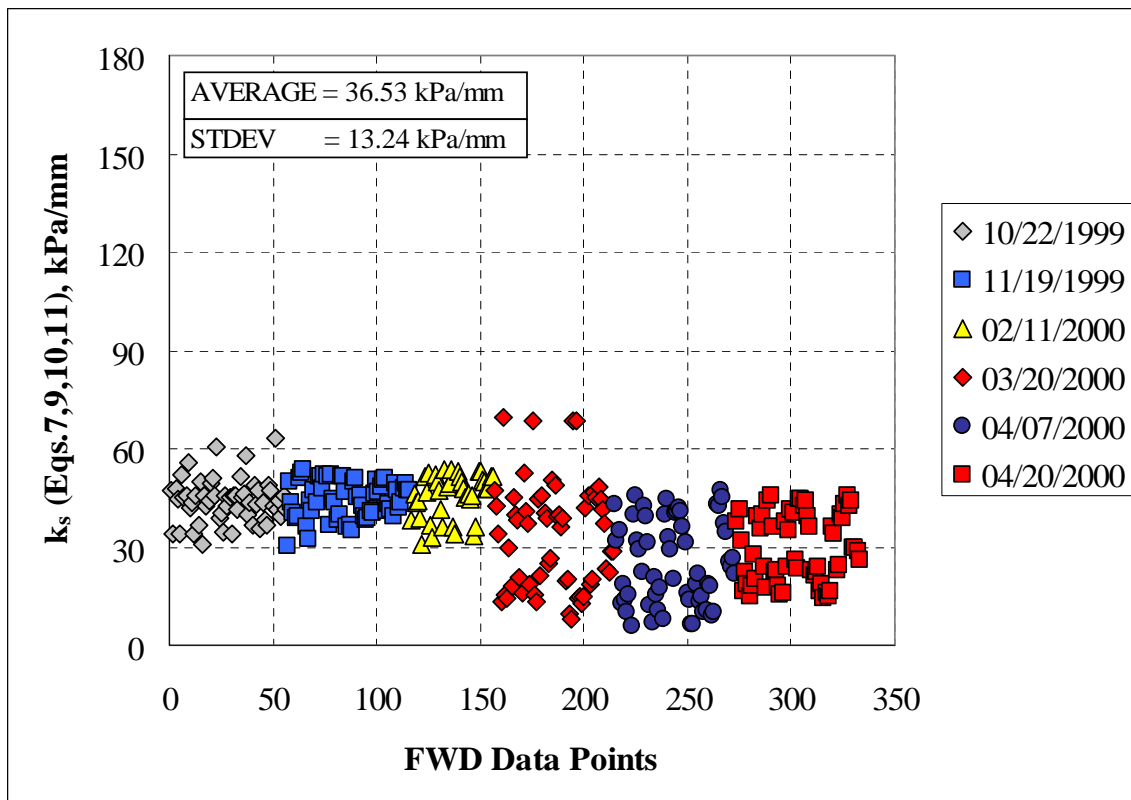
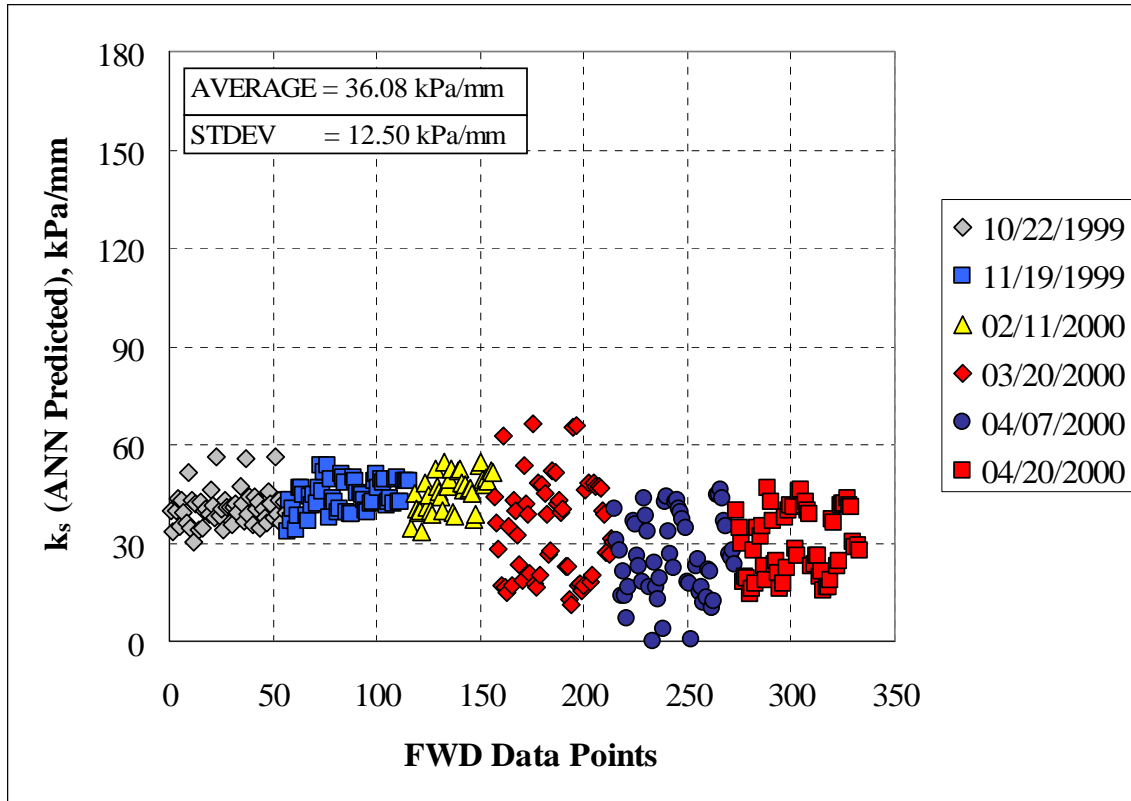


FIGURE 11 Coefficient of subgrade reaction predictions using: (a) BCM-ks-(6) ANN model, and (b) Closed-form equations.

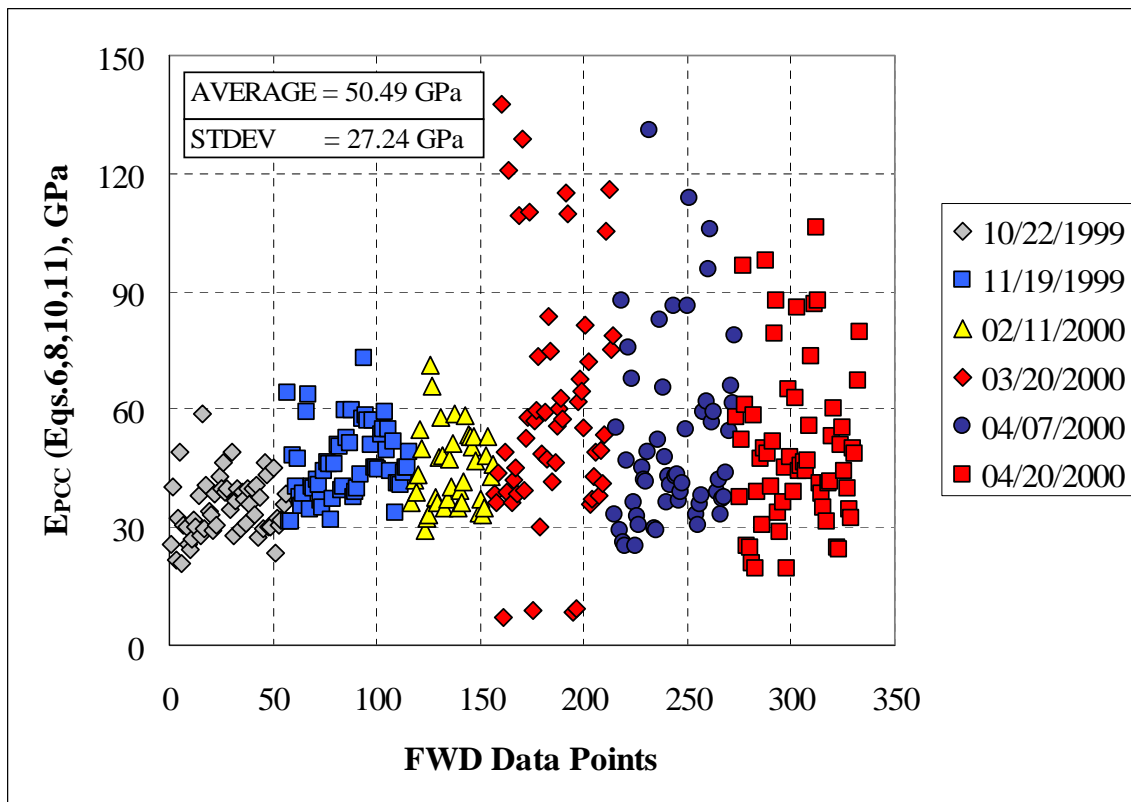
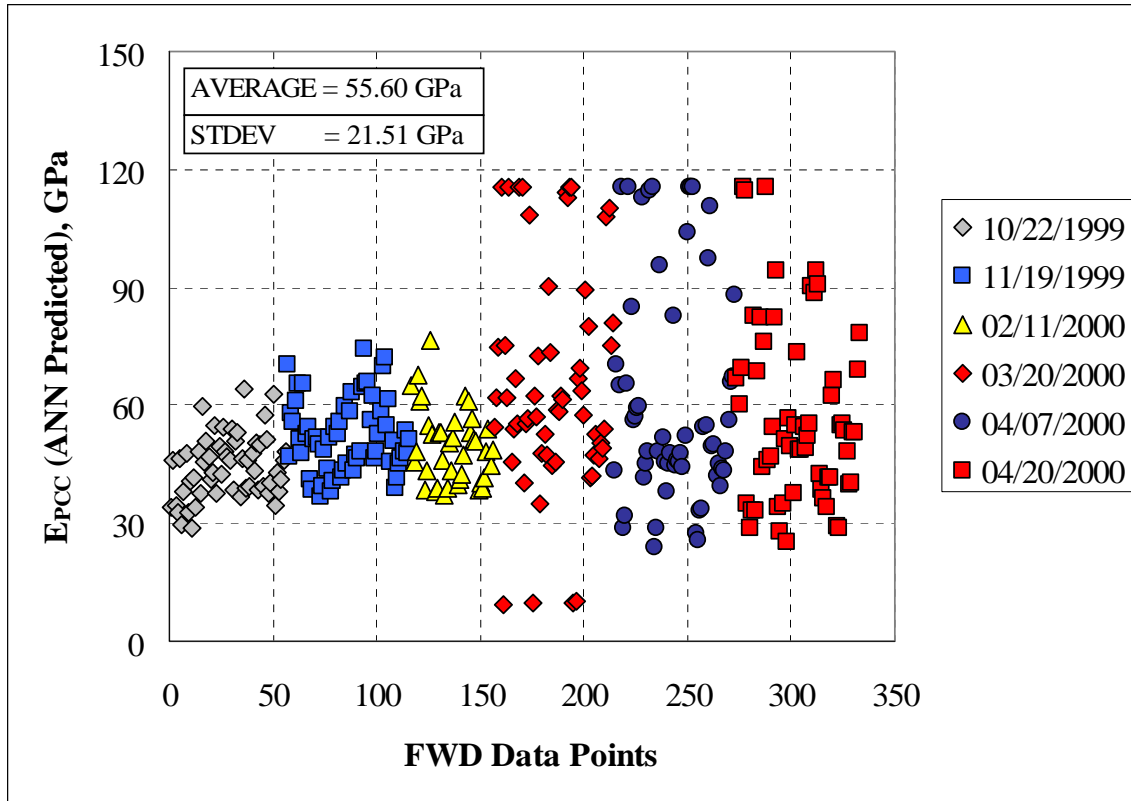


FIGURE 12 PCC layer elastic modulus predictions using: (a) BCM-EPCC-(4) ANN model, and (b) Closed-form equations.

Since the exact thickness of the PCC layer and the degree of bonding between the PCC and the Econocrete layers are not exactly known, more scatter is expected in E_{PCC} predictions. In addition, the time of the FWD/HWD testing is also crucial in the E_{PCC} backcalculation due to curling problems in rigid pavements. The results of previous studies indicate that the variations in temperature between two separate FWD tests affect primarily the elastic modulus of the slab (2). Due to the slab curling, temperature difference across the depth of the concrete pavement in the NAPTF-LRS section is another major reason of the scatter in E_{PCC} predictions (46). Therefore, the main reasons of the scatter in E_{PCC} predictions are basically the curling and warping issues, the bonding degree between the PCC and Econocrete layers, and the thickness of the PCC layer. To improve the E_{PCC} backcalculation, nondestructive evaluation techniques (NDT) such as Ground Penetrating Radar (GPR) readings or cores (destructive technique) can be taken along the test sections to determine the exact thickness of the layers at the FWD/HWD test points. Also, the time of the FWD tests due to curling and warping issues and the shape of the PCC slab should exactly be taken into account in the interpretations of the analyses of the concrete pavements.

CASE STUDY

The proposed artificial neural network models were also utilized to backcalculate the concrete pavement parameters for different FWD data sets obtained from four different counties in Iowa (Allamakee, Fayette, Franklin, and Wright Counties). The elastic modulus of the PCC layer and the coefficient of subgrade reaction predictions obtained from proposed ANN models are shown in Figure 13. The standard deviation values obtained from these analyses are very low and the predictions seem very consistent. All FWD test data was normalized to 40 kN (9-kip) in order to compare the results. There is no base layer in Allamakee and Fayette pavement test sections; therefore, PCC layer thickness was taken directly from the project files. On the other hand, there is 4 inches asphalt treated base (ATB) layer in Franklin and Wright Counties pavement test sections, and effective thickness value was calculated for these analyses by assuming 50% bonding degree (45). Also, the assumed elastic modulus values for the PCC and base layers for the effective thickness calculations are as follows: $E_{PCC} = 34.5$ GPa (5,000,000 psi), and $E_{base-ATB} = 6.9$ GPa (1,000,000 psi). The FWD deflection profiles seemed to be very erroneous were filtered from the analyzed database.

It should be also noted that coefficient of subgrade reaction (k_s) values show considerable seasonal changes throughout the year, and the time of the FWD testing used for the backcalculation of k_s should be taken into account in the design level. All FWD testings used in this case study were conducted in May, 2006. The average of the four backcalculated k_s value for 4 Iowa counties is approximately 40 kPa (≈ 150 psi/in) which Iowa – Department of Transportation (IA-DOT) pavement engineers approved.

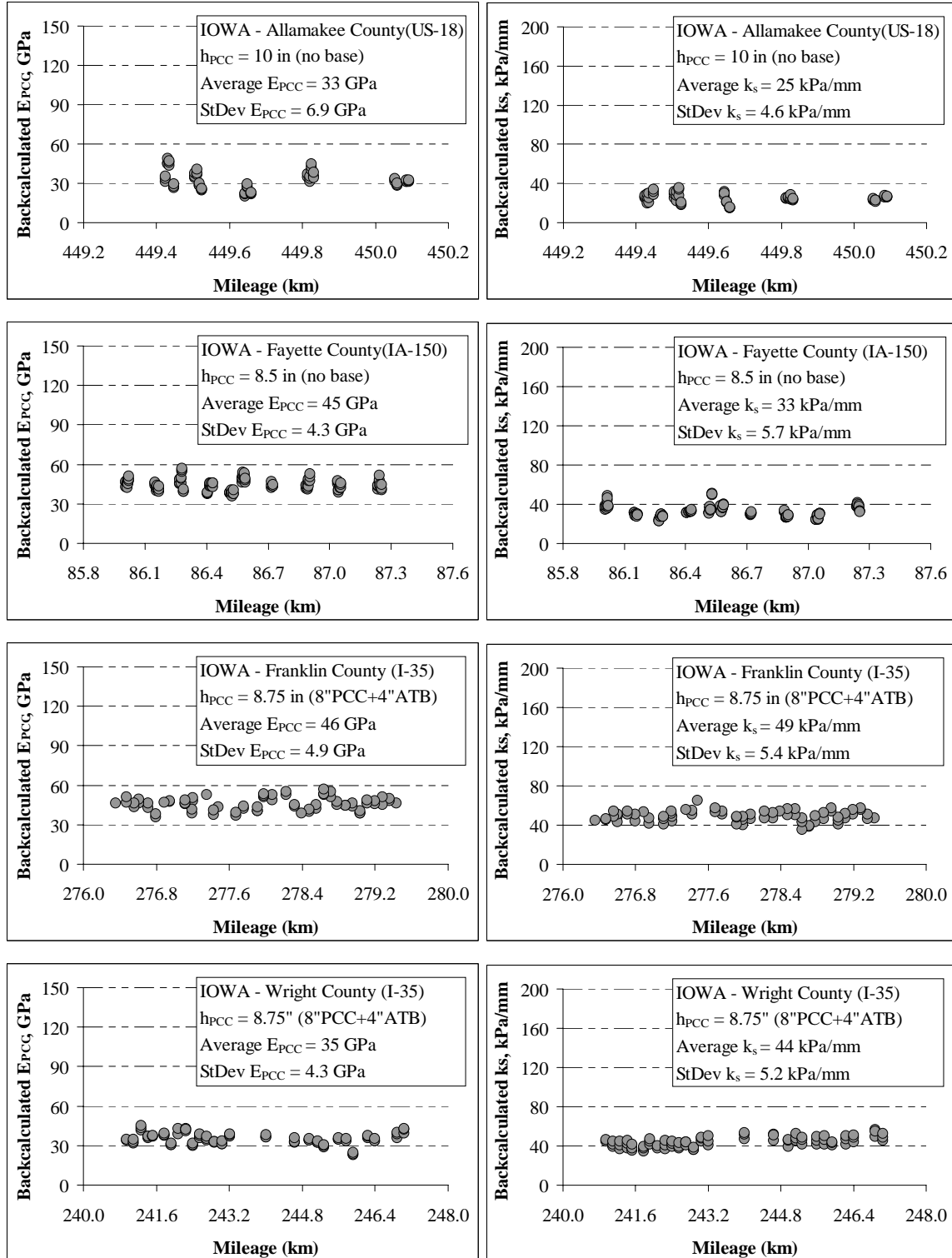


FIGURE 13 E_{PCC} and k_s predictions from the actual FWD deflection basin data.

CONCLUSIONS

The primary goal of this study was to show that artificial neural network (ANN) models could be developed to perform rapid and accurate predictions of PCC layer elastic modulus (E_{PCC}) and coefficient of subgrade reaction (k_s) values from FWD/HWD deflection data. ANN-based backcalculation models developed in this study successfully predicted the PCC layer elastic modulus and coefficient of subgrade reaction values from FWD/HWD deflection basins. In addition, a sensitivity study was conducted to show the effect of the PCC layer thickness on the backcalculation of the concrete pavement layer modulus. The results show that the backcalculated concrete pavement layer modulus is very sensitive to the PCC layer thickness whereas the coefficient of subgrade reaction is independent of this value. Based on the results of this study, the developed artificial neural network models can be utilized to predict the PCC layer modulus and the coefficient of subgrade reaction with very low average absolute error values (<0.4 % for the theoretical deflection basins). The use of the ANN-based models also resulted in a drastic reduction in computation time. Rapid prediction ability of the ANN models (capable of analyzing 100,000 FWD deflection profiles in one second) provides a tremendous advantage to the pavement engineers by allowing them to nondestructively assess the condition of the transportation infrastructure in real time while the FWD/HWD testing takes place in the field. Finally, it can be concluded that ANN-based analysis models can provide pavement engineers and designers with state-of-the-art solutions, without the need for a high degree of expertise in the input and output of the problem, to rapidly analyze a large number of rigid pavement deflection basins needed for project specific and network level pavement testing and evaluation.

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