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Neural Network-Based Approach for Analysis of Rigid Pavement Systems Using Deflection Data

M. Birkan Bayrak and Halil Ceylan

This paper focuses on the development of backcalculation models based on artificial neural networks (ANNs) for predicting the layer moduli of the jointed plain concrete pavements, that is, the elastic modulus of the portland cement concrete (PCC) layer and the coefficient of subgrade reaction for the pavement foundation. The ANN-based models were trained to predict the layer moduli by using 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 more than 20 years, has been employed as an advanced structural model for solving the responses of the rigid pavement systems and generating a 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 a single second) of the rigid pavement systems. The trained ANN-based models are capable of predicting the concrete pavement parameters with very low (<0.4%) average absolute error values. The ANN model predictions and closed-form solutions were compared through the use of the FWD deflection data, and the results are summarized in the 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 ANN-based models are capable of successfully predicting the rigid pavement layer moduli with high accuracy.

Falling-weight deflectometer (FWD) and heavy-weight deflectometer (HWD) testing have become the main nondestructive testing (NDT) techniques to evaluate structurally in-service pavements over the last 20 years. FWD testing is often preferred over destructive testing methods because FWD testing is faster than destructive tests and does 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 to supplement traditional destructive tests for pavement structural evaluation. Most important is the capability to gather data quickly at several locations while keeping a runway, taxiway, or apron operational during these 2- to 3-min tests, provided the testing is performed in close coordination with air traffic control. Without FWD–HWD testing, structural data must be obtained from numerous cores, borings, and excavation pits on existing highway or airport pavements. This can be very disruptive to highway and airport operations. FWD tests are economical to perform and data can be collected at up to 250 locations per day. FWD–HWD equipment measures pavement surface deflections from an applied dynamic load that simulates a moving wheel (1).

The elastic modulus of the portland cement concrete (PCC) slab, $E_{PCC}$, and the coefficient of subgrade reaction, $k_s$, are the backcalculated layer moduli parameters for the jointed plain concrete pavement (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 by using ILLI-SLAB (6), use of regression analysis to solve the AREA method for rigid pavements (7, 8), use of a best-fit algorithm to find the radius of relative stiffness ($f$) (8, 9), and many others.

The primary focus of this study is the backcalculation of the rigid pavement parameters with high accuracy by using artificial neural networks (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 using FWD data. FWD deflections and the PCC thickness of the test section are the only information needed for 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 with other methodologies. 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, for rapid analysis of a large number of rigid pavement deflection basins needed for project-specific and network-level pavement testing and evaluation.

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FINITE ELEMENT PROGRAMS FOR RIGID PAVEMENT SYSTEMS

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 (a) programs specifically designed for the analysis of pavement systems and (b) general-purpose programs. FE programs such as ABAQUS, ANSYS, and DYNA3D are powerful general-purpose programs with three-dimensional (3-D) nonlinear dynamic analysis capabilities. In several research studies, these programs have been used successfully for pavement analysis. A number of FE models built by means of these programs have been reported in the literature (10–12). In contrast, considerable computational resources and time needed for analysis of a structural system are among the limitations of the general-purpose FE programs.

FE-based programs developed specifically for analysis of concrete pavement systems include 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 multilayered loading of one- or two-layered medium-thick plates resting on a Winkler foundation or elastic solid (ISLAB2000, KENSLABS, WESLIQID). EverFE can analyze multilayered pavement systems by means of a 3-D-continuum brick element for the PCC and base layers. ISLAB2000 contains many advanced features that distinguish it from other pavement programs based on 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 for interpreting 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. For better understanding of the results produced by different programs, a sensitivity analysis was performed as part of this study.

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 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) and is an extension of elastic layer and plate theories. Several programs have been developed on the basis of the Burmister elastic layer solutions, but only DIPLOMAT can model pavement layers as plates, springs, and elastic layers together. However, 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.

In this study, plate theory was used in the analyses, and the pavement foundation is assumed to be a DL foundation (as in the Winkler-spring method). Different configurations of $E_{PCC}$, thickness of PCC layer ($h_{PCC}$), and $k_i$ were defined, and the $D_i$ deflections obtained from ISLAB2000, DIPLOMAT, and KENSLABS FE programs and Westergaard solutions were compared with each other (Figure 1). The deflection profiles obtained from ISLAB2000, DIPLOMAT, and KENSLABS FE models for three pavement configurations are also presented in Figure 1.

As Figure 1 shows, a good match was obtained for results from different models. Finally, a solution database using the ISLAB2000 FE model was created because ISLAB2000’s ease of modeling and...
flexibility in analysis are convenient compared with other methods. In contrast, there might be various reasons for the observed differences in the deflection profiles from different methods. These reasons are 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, while DIPLOMAT and Westergaard solutions consider a circular loading area.

**GENERATING ISLAB2000 FE SOLUTION DATABASE**

To train the ANN models, 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 × 6.1 m (20 × 20 ft) (Figure 2).

To maintain the same level of accuracy in the results from all analyses, a standard ISLAB2000 FE mesh was constructed for the slab. This mesh consisted of 10,004 elements with 10,209 nodes. The ISLAB2000 solution database was generated by varying the $E_{PCC}$, $k_s$, and $h_{PCC}$ 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 ratio ($\mu$), the slab width ($W$), the slab length ($L$), the PCC unit weight ($\gamma$), and the coefficient of thermal expansion ($\alpha$) were set equal to 0.15, 6.1 m (20 ft), 6.1 m (20 ft), 2,408.15 kg/m$^3$ (0.087 lb/in.$^3$), and $9.9 \times 10^{-6}/^\circ\text{C}$ ($5.5 \times 10^{-6}/^\circ\text{F}$), respectively.

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 (TRN) set of 49,539 (for $k_s$) and 39,026 (for $E_{PCC}$) and an independent testing (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 because many soil types exhibit nonlinear, stress-dependent elastoplastic behavior, especially under moving heavy wheel loads. Nevertheless,
experience in rigid pavements analysis and design has shown that
the 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 DL foundation is the most widely adopted mechanistic
idealization for analysis of concrete pavements (28). A DL
foundation is implemented in several FE models, including 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 co-
efficient of subgrade reaction, \( k_s \), which is the proportionality constant
between the applied pressure and the load plate deflection. Subgrade
defformations 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 the load (28).

ANNs AS PAVEMENT ANALYSIS TOOLS

There are several different types of ANNs, such as backpropagation
neutral networks (BPNN), radial basis function neural 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. The best-known
example of a neural network training algorithm is backpropagation,
which is based on a gradient descent optimization technique. The
backpropagation neural networks are described in many sources
(30–33). 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
epecially placed the emphasis on the successful use of neural
networks in geomechanical and pavement systems.

ANN-BASED PAVEMENT LAYER
BACKCALCULATION MODELS

Background

In this study, two groups of ANN-based backcalculation models
(BCM) were developed: BCM-\( k_s \) models and BCM-\( E_{\text{PCC}} \) models.
FWD deflection readings \( D_0 \) (0 mm), \( D_6 \) (203 mm), \( D_{12} \) (304 mm),
\( D_{18} \) (457 mm), \( D_{24} \) (610 mm), \( D_{28} \) (914 mm), \( D_{34} \) (1,219 mm),
and \( D_{48} \) (1,524 mm)] and PCC layer thickness \( h_{\text{PCC}} \) 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 \( E_{\text{PCC}} \) values (Table 2).

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 the networks’
better ability to facilitate the nonlinear functional mapping (26, 34).
ANN architectures, input parameters, output variables, and average
absolute error (AAE) values of all developed models are tabulated
in Table 2. The comparison of the ISLAB2000 solutions and ANN
predictions for \( k_s \) and \( E_{\text{PCC}} \) are shown in Figures 3 and 4, respectively.
Furthermore, Figure 5 shows the training and testing mean squared
error progress curves for the BCM-\( k_s \)-(6) and BCM-\( E_{\text{PCC}} \)-(4) models.

SIGNIFICANCE OF THICKNESS AND
LAYER BONDING IN PAVEMENT
LAYER BACKCALCULATION

Two of the important issues in the backcalculation of the rigid pave-
ments parameters are the degree of bonding between layers and the
thickness of the PCC and base layers. To simplify the ANN-based
backcalculation methodology developed in this study, only one thick-
ness 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.
Because it is difficult to construct a long pavement section with a
uniform thickness value, it is assumed during the backcalculation of
the pavement parameters that pavement thickness is uniform for a
given section, and it is 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 (35).

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

\[
h_{\infty} = \left( h_1^2 + \frac{E_2}{E_1} h_2^2 + 12 \left( \frac{x_{50} - h_1}{2} \right)^2 \left( h_1 + \frac{E_2}{E_1} \left( h_1 - x_{50} + \frac{h_1}{2} \right) h_2 \right) \right)^{1/2}
\]

TABLE 2  ANN Architectures and Average Absolute Error (AAE) Values for
ANN-Based Backcalculation Models

<table>
<thead>
<tr>
<th>ANN Model</th>
<th>Input Parameters</th>
<th>ANN Architecture</th>
<th>AAE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCM-( k_s )-(4)</td>
<td>( D_0 ), ( D_6 ), ( D_{12} ), ( D_{18} )</td>
<td>4-60-60-1</td>
<td>0.28</td>
</tr>
<tr>
<td>BCM-( k_s )-(6)</td>
<td>( D_0 ), ( D_6 ), ( D_{12} ), ( D_{18} ), ( D_{24} ), ( D_{34} )</td>
<td>6-60-60-1</td>
<td>0.20</td>
</tr>
<tr>
<td>BCM-( k_s )-(7)</td>
<td>( D_0 ), ( D_6 ), ( D_{12} ), ( D_{18} ), ( D_{24} ), ( D_{34} ), ( D_{48} )</td>
<td>7-60-60-1</td>
<td>0.19</td>
</tr>
<tr>
<td>BCM-( k_s )-(8)</td>
<td>( D_0 ), ( D_6 ), ( D_{12} ), ( D_{18} ), ( D_{24} ), ( D_{34} ), ( D_{48} ), ( D_{60} )</td>
<td>8-60-60-1</td>
<td>0.22</td>
</tr>
<tr>
<td>BCM-( E_{\text{PCC}} )-(4)</td>
<td>( D_0 ), ( D_{12} ), ( D_{24} ), ( D_{34} ), ( h_{\text{PCC}} )</td>
<td>5-60-60-1</td>
<td>0.34</td>
</tr>
<tr>
<td>BCM-( E_{\text{PCC}} )-(6)</td>
<td>( D_0 ), ( D_{12} ), ( D_{24} ), ( D_{34} ), ( D_{48} ), ( D_{60} )</td>
<td>7-60-60-1</td>
<td>0.32</td>
</tr>
<tr>
<td>BCM-( E_{\text{PCC}} )-(7)</td>
<td>( D_0 ), ( D_{12} ), ( D_{24} ), ( D_{34} ), ( D_{48} ), ( D_{60} )</td>
<td>8-60-60-1</td>
<td>0.29</td>
</tr>
<tr>
<td>BCM-( E_{\text{PCC}} )-(8)</td>
<td>( D_0 ), ( D_{12} ), ( D_{24} ), ( D_{34} ), ( D_{48} ), ( D_{60} )</td>
<td>9-60-60-1</td>
<td>0.30</td>
</tr>
</tbody>
</table>
FIGURE 3 Prediction performances of ANN-based models for backcalculating coefficient of subgrade reaction, $k_s$.

FIGURE 4 Prediction performances of ANN-based models for backcalculating PCC layer modulus, $E_{PCC}$. 

AAE = 0.28 %
Testing Set=2,000
BCM-$k_s$-(4)

AAE = 0.20 %
Testing Set=2,000
BCM-$k_s$-(6)

AAE = 0.19 %
Testing Set=2,000
BCM-$k_s$-(7)

AAE = 0.22 %
Testing Set=2,000
BCM-$k_s$-(8)

AAE = 0.34 %
Testing Set=2,000
BCM-$E_{PCC}$-(4)

AAE = 0.32 %
Testing Set=2,000
BCM-$E_{PCC}$-(6)

AAE = 0.29 %
Testing Set=2,000
BCM-$E_{PCC}$-(7)

AAE = 0.30 %
Testing Set=2,000
BCM-$E_{PCC}$-(8)
Effective thickness for unbonded PCC layers was computed with the following equation:

$$h_{e,u} = \left( 1 - x \right) h_{e,b} + x \left( h_{e,u} - h_{e,b} \right)$$

where

$$h_{e,b} = \text{effective thickness of the fully bonded PCC layers},$$

$$h_{e,u} = \text{effective thickness of the unbonded PCC layers},$$

$$h_{e,p} = \text{effective thickness of the partially bonded PCC layers},$$

$$E_1 \text{ or } E_2 = \text{elastic modulus for Layer 1 or 2},$$

$$h_1 \text{ or } h_2 = \text{thickness for Layer 1 or 2},$$

$$x_{na} = \text{neutral axis distance from top of layer},$$

$$x = \text{degree of bonding (ranges between 0 and 1)}.$$

Effect of Layer Thickness in $E_{PCC}$ 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 (Figure 6a).

Effect of Pavement Layer Bonding in $E_{PCC}$ Predictions

The LRS (rigid pavement with stabilized base over low-strength subgrade) data were 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 were assumed as follows: $E_{PCC} = 34.5 \text{ GPa } (5 \times 10^6 \text{ psi})$, $E_{base} = 6.9 \text{ GPa } (1 \times 10^6 \text{ psi})$, $h_{PCC} = 28 \text{ cm (11 in.)}$, and $h_{base} = 15.6 \text{ cm (6 1⁄8 in.)}$. 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 by means of the equations given above. The variation of the backcalculated $E_{PCC}$ values for the LRS section is presented in Figure 6b.
As Figure 6b shows, the 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 \(E_{\text{PCC}}\) value 17 GPa (2.5 \(\times\) 10^6 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 effective pavement thickness in the \(E_{\text{PCC}}\) 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; \(\ell\) can be calculated from the AREA–\(\ell\) equations. AREA value was calculated from four deflections \((D_6, D_{12}, D_{18},\) and \(D_{24})\) and six deflections \((D_6, D_{12}, D_{18}, D_{24}, D_{36},\) and \(D_{60})\) as shown in Equations 6 and 7 below. Load \((P)\), radius of load plate \((a)\), and Poisson ratio \((\mu)\) were set to 40 kN (9 kips), 150 mm (5.9 in.), and 0.15, respectively. The equations used in the numerical backcalculation of the rigid pavement parameters are summarized below:

\[
\text{AREA}_1 \text{(in.)} = 6 \left[ 1 + 2 \left( \frac{D_6}{D_9} \right) + 2 \left( \frac{D_{12}}{D_9} \right) + \left( \frac{D_{18}}{D_9} \right) \right] \quad (6)
\]

\[
\text{AREA}_2 \text{(in.)} = 6 \left[ 1 + 2 \left( \frac{D_6}{D_9} \right) + 2 \left( \frac{D_{12}}{D_9} \right) + 2 \left( \frac{D_{18}}{D_9} \right) \right] + 2 \left( \frac{D_{24}}{D_9} \right) + \left( \frac{D_{36}}{D_9} \right) \quad (7)
\]

\[
\ell_s \text{(in.)} = (-128.9885) + (5.4082 \times \text{AREA}_1) + (1.0224 \times (\text{AREA}_1 - 30.8637)^3) + (0.1919 \times (\text{AREA}_1 - 30.8637)^3) + (0.0146 \times (\text{AREA}_1 - 30.8637)^3) \quad (8)
\]

\[
\ell_e \text{(in.)} = (-49.1501) + (1.9801 \times \text{AREA}_2) + (0.11467 \times (\text{AREA}_2 - 44.3008)^3) + (0.0075 \times (\text{AREA}_2 - 44.3008)^3) + (0.0002 \times (\text{AREA}_2 - 44.3008)^3) \quad (9)
\]

\[
k_s = \left( \frac{P}{8D_6\ell_s^2} \right) \left[ 1 + \left( \frac{1}{2\pi} \right) \ln \left( \frac{a}{2\ell_s} \right) - 0.673 \left( \frac{a}{\ell_s} \right)^3 \right] \quad (10)
\]

\[
E_{\text{PCC}} = \frac{12\ell_s^2 k_s (1 - \mu^2)}{h_{\text{PCC}}} \quad (11)
\]

**VALIDATION OF ANN-BASED MODELS: COMPARISON OF ANN-BASED MODELS WITH CLOSED-FORM EQUATIONS**

To validate the ANN-based backcalculation models, ANN model predictions were compared with the closed-form equation results by using the FWD–HWD test data collected from NAPTF. The FWD–HWD deflection profiles obtained from the NAPTF’s LRS test sections are depicted in Figure 7.

All FWD–HWD test results were normalized to 40 kN (9 kips) to compare the results. The ANN BCM-\(k_s\)-(6) model predictions and closed-form equation solutions (Equations 7, 9, and 10) are presented in Figure 8a for backcalculation of \(k_s\) by use of the NAPTF–LRS FWD data. In addition, ANN BCM-\(E_{\text{PCC}}\)-(4) model predictions and closed-form equation solutions (Equations 6, 8, 10, and 11) were compared and results are presented in Figure 8b for backcalculating the \(E_{\text{PCC}}\) value by use of the same FWD data. The layers were assumed fully bonded in this analysis. As one can see 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, one can conclude 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 (Figure 7). Higher scattering in \(E_{\text{PCC}}\) predictions can be explained by \(E_{\text{PCC}}\) being dependent on the PCC layer thickness and the degree of bonding between the PCC and the Econocrete base layers.

Because 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 \(E_{\text{PCC}}\) predictions. In addition, the time of the FWD–HWD testing is also crucial in the \(E_{\text{PCC}}\) backcalculation due to curling and warping problems in rigid pavements. The results of previous studies indicate that the variations in temperature and moisture between two separate FWD tests affect primarily the elastic modulus of the slab \((E)\). Because of slab curling and warping, temperature and moisture differences across the depth of the concrete pavement in the NAPTF–LRS section are another major reason for the scatter in \(E_{\text{PCC}}\) predictions \((36)\). Therefore, the main reasons for the scatter in \(E_{\text{PCC}}\) predictions are the curling and warping of the plates, the degree of bonding between the PCC and Econocrete layers, and the thickness of the PCC layer. To improve further the \(E_{\text{PCC}}\) backcalculation accuracy, NDT techniques, such as ground penetrating radar (GPR) readings, or cores (destructive technique) can be used along the pavement sections to determine the exact thickness of the layers at the FWD–HWD test points. In addition, the testing time of the FWD tests due to diurnal changes (curling and warping of the slabs due to temperature and moisture fluctuations) and the initial shape of the PCC slab (built-in curling and warping due to drying shrinkage, etc.) should be taken into account in the interpretation of the deflection data analysis.

**CONCLUSIONS**

The primary goal of this study was to show that ANN models could be developed to perform rapid and accurate predictions of PCC layer elastic modulus \((E_{\text{PCC}})\) 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 and bonding degree on the backcalculation of the concrete pavement layer modulus. The results showed that the backcalculated concrete pavement layer modulus was very sensitive to the PCC layer thickness and bonding degree, whereas the coefficient of subgrade reaction was independent of these values. The results of this study make clear that the developed ANN models can be used to predict the PCC layer modulus and the coefficient of subgrade reaction with very low AAE values (<0.4% for the theoretical deflection basins). The use of the ANN-based models also resulted in a drastic reduction in computation time.
FIGURE 7  FWD–HWD deflection basins normalized to 40-kN load level for NAPTF–LRS section.
time. The rapid prediction ability of the ANN models (capable of analyzing 100,000 FWD deflection profiles in 1 s) provides a tremendous advantage to 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 analyze rapidly a large number of rigid pavement deflection basins needed for project-specific and network-level pavement testing and evaluation.

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