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Development of rigid airfield pavement foundation response and moduli prediction models

by

Adel Rezaei Tarahomi

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Civil Engineering (Civil Engineering Materials)

Program of Study Committee:
Halil Ceylan, Major Professor
Bora Cetin
Kristen Sara Cetin

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2019

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DEDICATION

To my wonderful wife and best friend, Zahra, who always inspires me with love, kindness, patience, and confidence.

To my beloved father and mother whose endless love, encouragement, prays of day and night, and supports make me thankful and satisfied with my achievements.

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ABSTRACT

Designing the pavement foundation for rigid airfield pavements and understanding the contribution of pavement foundation elements to overall pavement performance and pavement failure have been challenges for the rigid airfield pavement design community. While many models have been developed to best simulate pavement foundation behavior for rigid airfield pavements, many of them have focused only on the failure of the Portland Cement Concrete (PCC) layer and did not sufficiently consider the contribution of pavement foundation to the failure. The Federal Aviation Administration's (FAA's) pavement design software, FAARFIELD, considers the maximum horizontal stress at the bottom edge of the concrete slab for the bottom-up cracking failure of a PCC layer but does not consider the critical responses for the failure of subbase and subgrade layers in rigid pavement design. Incorporating critical pavement foundation responses into pavement design procedures is of great interest. The primary objective of this research study is to investigate the feasibility of developing rapid three-dimensional finite-element (3D-FE)-based pavement foundation response and moduli prediction models for the design of both new and rehabilitated rigid airfield pavement structures. The three case studies investigated in the development of the models include: (1) rigid pavement foundation response prediction models for different wide-body aircraft loading conditions, (2) rigid pavement foundation response prediction models for Heavy/Falling Weight Deflectometer (H/FWD) loading conditions, and (3) single rigid-pavement moduli prediction model. The development procedure and results based on rapid 3D-FE based prediction models are presented in this thesis along with other significant findings and recommendations for employing the developed models in the

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structural design and evaluation of rigid airfield pavement systems. It was found that the developed models could successfully predict 3D-FE pavement solutions for all cases investigated in this study, could account for rigid pavement foundation-related distresses, and could be potentially integrated into FAARFIELD as surrogate forward response prediction models in the future.

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CHAPTER 1. INTRODUCTION

In rigid airfield pavement design, the pavement foundation typically consists of a base course, a subbase course and a subgrade (FAA 2016). Base courses can be divided into unstabilized and stabilized categories. Unstabilized base courses are typically composed of crushed and uncrushed aggregates, while stabilized base courses are composed of crushed and uncrushed aggregates stabilized with cement or asphalt. In addition, subbase courses typically use granular material that could be either unstabilized or stabilized. Finally, a typical subgrade is composed of either natural or modified soils.

A base layer is used in rigid airfield pavement to provide a uniform and stable support for rigid pavement slabs. Selection of base layer types along with minimum base thickness requirements vary based on maximum airplane gross weight while operating on pavement (FAA 2016). For example, a stabilized base is required when pavements are designed to serve airplanes weighing more than 45.4 metric tons (100,000 lb.), while below that weight pavements do not require use of a stabilized base. A minimum of 127 mm. (5 in.) of stabilized base and a minimum of 152.4 mm. (6 in.) crushed aggregate base thicknesses are also required when pavements are designed for serving airplanes over 45.4 metric tons (100,000 lb.).

FAARFIELD, FAA's pavement design software included in FAA AC 150/5320-6F (FAA 2016) allows users to consider up to three base/subbase layers in rigid pavement design procedures. Base/subbase layer material properties are characterized by modulus and Poisson's ratio values. The modulus and Poisson ratio values for standard materials (e.g., P-401 and P-403 defined in FAA AC 150/5370-10G (FAA 2014)) are directly assigned by the software and cannot be modified by the user. However, the software does allow users to

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change the modulus input of a layer while displaying a warning that a 'non-standard' material has been used. The use of non-standard material requires FAA approval before its use.

A subgrade layer is characterized by its modulus of subgrade reaction, its k or elastic (Young's) modulus E_{SG}, and its Poisson's ratio, v. While either k or E_{SG} can be input to the software, FAARFIELD will use only E_{SG} in structural computations. If the foundation modulus is entered into the software as a k value, it will be converted into E_{SG} using the following equation (Equation 1) (FAA 2016):

$$E_{SG} = 20.15 \times k^{1.284} \quad (1)$$

Where E_{SG} = Elastic modulus (E-modulus) of the subgrade in psi and k = Modulus of subgrade reaction of the subgrade in psi/in.

FAARFIELD employs a three-dimensional finite-element (3D-FE)-based engine (NIKE3D_FAA, abbreviated as NIKE3D) to compute concrete pavement responses. The FAA has also developed FEAFAA (Finite Element Analysis – FAA) that uses NIKE3D as a stand-alone tool for 3D-FE analysis of multiple-slab rigid airport pavements and overlays. It computes responses (deflections, stresses, and strains) of rigid pavements under the individual aircraft landing-gear loads. However, FAARFIELD considers only the maximum horizontal stress at the bottom edge of the concrete slab in determining bottom-up cracking failure of PCC layer but does not take into account the critical responses for failure of subbase and subgrade layers in rigid pavement designs. It is obvious that incorporating such pavement foundation responses into pavement design procedures would be of great interest.

The Falling Weight Deflectometer (FWD) has been used to assess the structural integrity of existing pavements, to determine the material properties of in-situ pavement and

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subgrade layers for design of rehabilitated pavement structures, and to compare relative strengths and/or conditions with respect to other sections of a pavement system (FAA 2016). For evaluating airfield pavement systems, a Heavy Weight Deflectometer (HWD) device, similar to a FWD testing, but having higher load levels, is used. These tests are performed by applying impulse loads to a pavement surface through circular metal plates and measuring pavement surface deflections resulting from the impulse load at several radial offsets. The extent and variation of the measured deflections are indicators of pavement system response to the applied load. The distribution of deflections by offsets (deflection basin) is predominantly a function of the thickness of the pavement layers, the moduli of individual layers, and the magnitude of the load (Gopalakrishnan et al. 2006). Knowing the measured deflections of the pavement system and the layer thicknesses, the elastic (Young's) moduli of individual pavement layers can be estimated through a process called *backcalculation*.

The BAKFAA, FAA's backcalculation software accompanying FAA AC 150/5370-11B (FAA 2011), performs backcalculation using a mathematical model of a pavement system (forward model) that considers theoretical deflection values and assumed initial layer moduli values (i.e., seed moduli values) under the applied load. By changing the layer moduli, the calculated deflections can then be compared with the measured deflection values until these two deflection values match within a certain tolerance limit (Gopalakrishnan et al. 2006). The back-calculated pavement moduli values could be input directly into FAARFIELD for design of rehabilitated airfield pavement structures. The BAKFAA uses elastic-layered analysis for the forward model in its backcalculation. Although the FAA recommends using backcalculation methods consistent with the forward computational procedure used for structural evaluation and design, there is no backcalculation tool available

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consistent with NIKE3D, a 3D-FE-based pavement response model for design of new and rehabilitated (i.e., using overlays of existing concrete pavements) rigid pavement structures. Long and unpredictable computation times (i.e., 16 minutes for a case subjected to the mechanical and thermal loading for a nine-slab system, using a regular desktop computer) are major concerns when employing NIKE3D as a forward model for a backcalculation tool.

Machine learning, as an alternative to the conventional engineering methods, can be used for solving many civil engineering problems such as determining infrastructure resilience in disasters to studying pavement deteriorations (Nazarnia and Sarmasti 2018, Fathi et al. 2019). ANNs, as a machine learning method, are very useful tools that can be have for a long time been successfully used in solving pavement engineering problems (Ceylan et al. 2014). ANNs are useful in modeling pavement systems because they have few of the limitations of conventional techniques such as normality, linearity, and variable independence. Moreover, ANNs can capture complex linear and nonlinear relationships between dependent and independent variables in a small fraction of time. Ceylan et al. (1999) and Ceylan (2002) demonstrated the success of ANN-based surrogate response models in computing lateral and longitudinal tensile stresses as well as deflections at the bottom of jointed concrete airfield pavements as a function of type, level, and location of an applied gear load, slab thickness, slab modulus, subgrade support, pavement temperature gradient, load-transfer efficiencies, and so on.

Ceylan et al. (2005) developed ANN models to predict stiffness properties of rigid airfield pavements (slab-on-grade concrete pavement) using results from an ISLAB 2000 finite-element program. The predictions from the models compared favorably with real HWD data gathered at FAA's National Airport Pavement Test Facility (NAPTF) test sections.

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Objectives

The primary objective of this study is to investigate the feasibility of developing rapid three-dimensional finite-element (3D-FE)-based pavement foundation response and moduli prediction models for design of new and rehabilitated rigid airfield pavement structures. The developed prediction models use Artificial Neural Networks (ANNs) to return a close estimate of the responses computed by NIKE3D employed in FAARFIELD. Three case studies investigated in developing the ANN models include: (1) rigid-pavement foundation response prediction models for different aircraft loading conditions, (2) rigid-pavement foundation response prediction models for HWD/FWD loading conditions, and (3) single rigid-pavement moduli prediction model. The development procedure and results from rapid 3D-FE based ANN prediction models are presented in this thesis along with other significant findings and recommendations for employing the developed models in structural design and evaluation of rigid airfield pavement systems.

Thesis Organization

Chapter 1 presents the background, motivations, objectives, and the thesis organization. Chapter 2 describes methodology for developing database and 3-D finite element simulations for training ANN models. Chapter 3 discusses about developing ANN models for pavement foundation critical responses under two heavy aircraft (B777-300 ER and A380-800) loading. Chapter 4 presents the ANN models predicting pavement foundation responses under HWD loading. Chapter 5 presents backcalculation models which can replicate the pavement layers’ elastic modulus. Finally, chapter 6 summarizes all the finding of this study and presents some recommendation to continue and expand this study.

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CHAPTER 2. METHODOLOGY

Figure 2.1 shows the overall description of the ANN model development approach used in this study. Initially, a finite element based knowledge database composed of randomly generated FEAFAA input parameters within the minimum and maximum predefined limits, and FEAFAA-produced pavement responses for each pavement layer were populated to develop the ANN models. This finite element based knowledge database was then employed in ANN model development to establish the relationships between the input parameters and output variables.

Finite element based knowledge database development

- Populate randomly generated FEAFAA input parameters within specified ranges
- Run FEAFAA one case at a time
- Extract critical pavement responses for each pavement foundation sublayer (Extract deflections in offsets for FWD/HWD cases
- Enter the extracted critical pavement responses to the database

ANN model development

- Develop ANN models using FEAFAA input parameters as inputs and extracted critical pavement responses for each pavement foundation sublayer as outputs (Case 1)
- Develop ANN models using FEAFAA input parameters as inputs extracted deflection values in radial offsets for each layer as outputs (Case 2)
- Develop ANN models using extracted deflection values in radial offsets along with other FEAFAA input parameters (not including modulus values) as inputs and modulus values in each pavement foundation sublayer as outputs (Case 3)

Figure 2.1 *Overall description of ANN model development approach.*

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Finite Element Based Knowledge Database Development

To develop the finite element based knowledge database, the required input parameters and their ranges were required. The FEAFAA required inputs related to aircraft type selection, pavement structure including material properties, layer thicknesses, slab and mesh sizes, loading positions, slab temperature gradient through the slab thickness (if temperature gradient loading is selected) and joint modeling. For each parameter, FEAFAA provides hardcoded range limits. In developing the database, 500 samples (cases) were populated using randomly assigned numbers within the predefined ranges for each input parameter. These predefined ranges were based on a combination of FEAFAA's hardcoded ranges and engineering judgment. Table 2.1 shows the inputs and their ranges used in the development of the finite element based knowledge database. The loading angle in the table 1 is angle of inclination symmetry axis of the airplane gear and the Y-axis. Note that ANN models were developed for rigid pavement configurations consisting of a PCC slab layer, a strong base layer (either a cement or asphalt treated base), a weak subbase (e.g., granular), and a subgrade. Since the current version of the only software for analyzing rigid airfield pavements of the FAA (FEAFAA) is using isotropic linear elastic assumption of the pavement layers, the ANN models in the current study have been developed based on this assumption. However, the authors are able to develop ANN models for more complicated FEM solutions based on their experience in past related studies. The authors are completely aware of the importance of the nonlinear, stress-dependent stiffness of the unbound aggregate base and subgrade soil layers for designing full-depth and conventional asphalt pavements. Such nonlinear, stress dependent characterizations of geomaterial layer stiffness also need to be properly accounted for in the nondestructive evaluation of existing pavements, i.e. the backcalculation of layer moduli from FWD/HWD testing (Ceylan et al. 2005).

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Gopalakrishnan et al. (2006) mapped the solutions of nonlinear, stress-dependent finite element runs using ANNs and compared the ANN-based predictions of the flexible pavement layer moduli with the results obtained from the backcalculation programs using linear elastic assumption of the flexible pavement layers. Ceylan et al. (2005) developed ANN based backcalculation and forward calculation pavement structural models using the ILLI-PAVE 2000 full-depth asphalt finite element solutions with nonlinear, stress-dependent subgrade soil properties. Both studies has shown that ANNs are capable of mapping complex relationships, such as those studied in complex finite element analyses, between the input parameters and the output variables for nonlinear, stress-dependent systems.

Table 2.1 *Ranges of input parameters used for producing finite element analysis runs.*

Inputs		Ranges	
		Min	Max
PCC Slab	Modulus (GPa) (psi)	20.7 (3×10^6)	48.3 (7×10^6)
	Thickness (cm.) (in.)	15.2 (6)	60.9 (24)
	Poisson Ratio	0.10	0.20
Base	Modulus (GPa) (psi)	1.4 (2×10^5)	13.8 (2×10^6)
	Thickness (cm.) (in.)	10.0 (4)	76.2 (30)
	Poisson Ratio	0.15	0.25
Granular Subbase	Modulus (GPa) (psi)	1×10^{-1} (15,000)	5.2×10^{-1} (75,000)
	Thickness (cm.) (in.)	15.2 (6)	127 (50)
	Poisson Ratio	0.20	0.40
Subgrade	Modulus (GPa) (psi)	2.1×10^{-2} (3,000)	3.4×10^{-1} (50,000)
	Poisson Ratio	0.30	0.45
Slab Dimension (m.) (ft.)		4.6 (15)	9.1 (30)
Slab Number of Elements		30	
Number of Slabs		9	
Foundation Number of Elements		30	
Loading Angle		0	90
Temperature Gradient (°C/cm) (°F/in.)		-0.3 (-2)	+0.3 (2)
Thermal Coefficient (1/ °C) (1/°F)		7.4×10^{-6} (4.1×10^{-6})	12.9×10^{-6} (7.2×10^{-6})
Equivalent Joint Stiffness (kPa) (psi)		85,557 (12,409)	4,089,921 (593,193)

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The FEAFAA software performs a 3D-FE analysis in which slab and pavement foundation layers are divided into meshes whose number is defined by the user. At the end of the analysis, the software produces an output file in txt format that provides data regarding x, y, and z coordinates for each mesh node as well as computed stress information at each mesh node. Figure 2.2 shows a typical FEAFAA output (subjected to a simultaneous Boeing B777-300ER mechanical load and a thermal load) plotted using Tecplot 360 software [1].

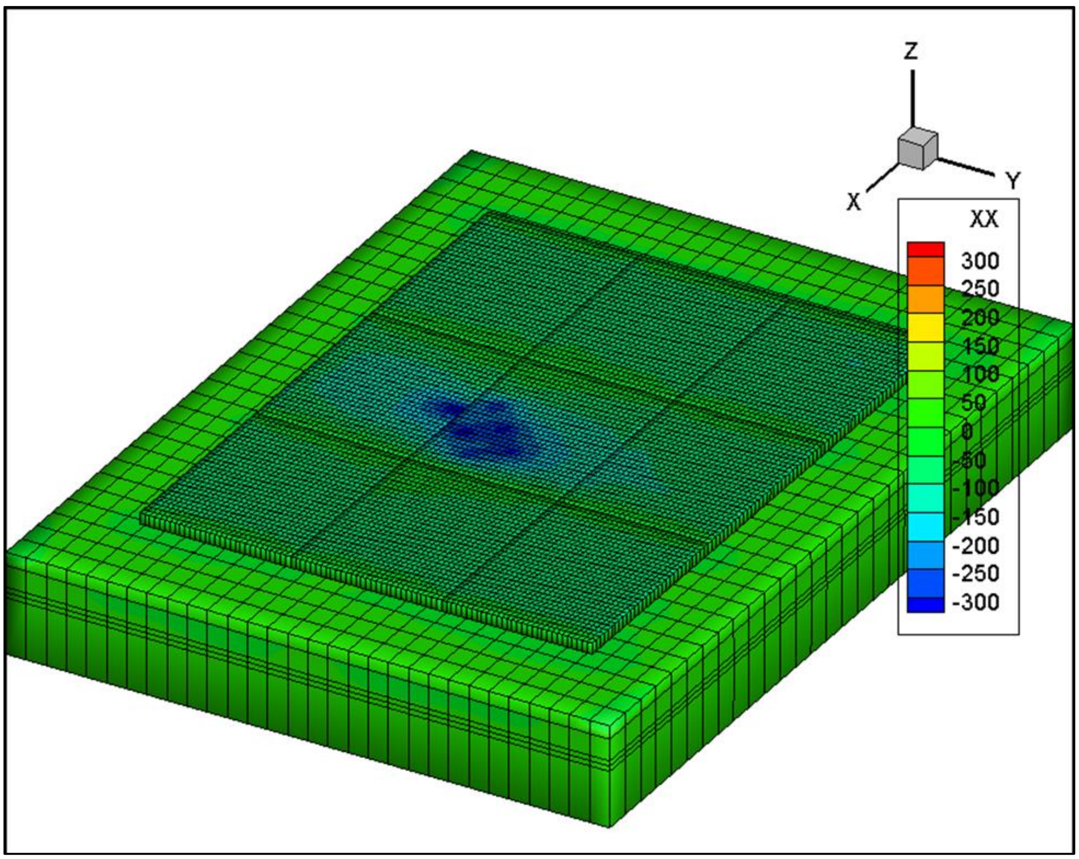

Figure 2.2 *A FEAFAA output (bending stresses).*

In this study, an automation tool was also developed using the C# programming tool together with the AutoIt® scripting tool; it can perform batch runs, obtain outputs, and perform post-processing that includes extracting critical pavement responses for each pavement foundation sublayer and adds them into the finite element based knowledge database. Figures 2.3 and 2.4 show the automation tools developed for this study.

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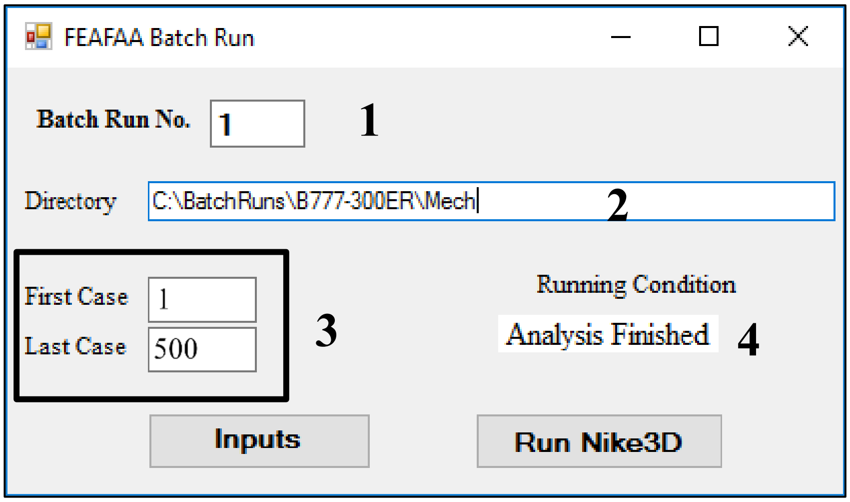
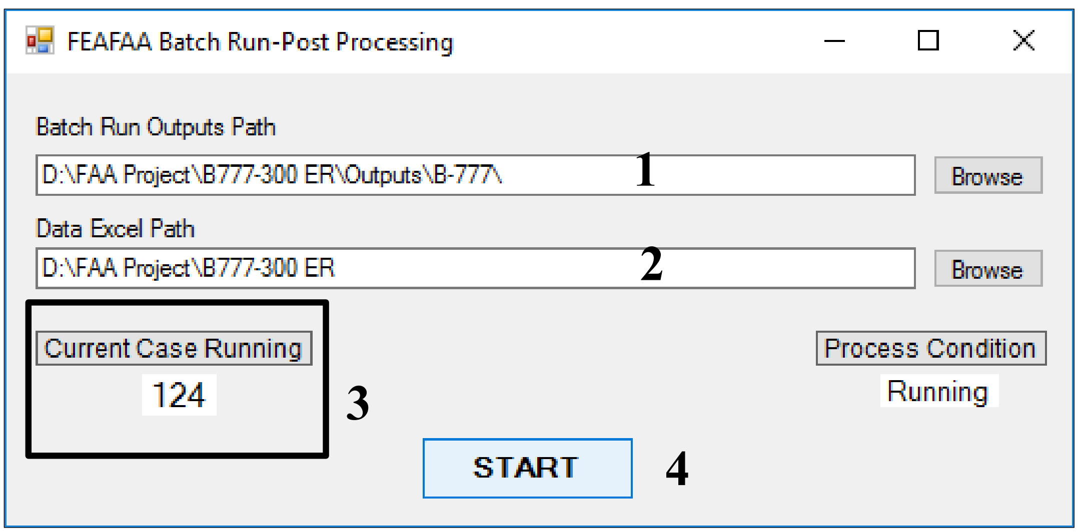


1. Batch run number for multiple runs
2. Directory of FEAFAA, inputs, and outputs
3. Range of cases for running in FEAFAA
4. Shows which case is running or finished

Figure 2.3 *Graphical interface of batch run program.*



1. Directory of output files generated by NIKEPLOT
2. Directory of datasets spreadsheet
3. Currently running case
4. Start post-processing

Figure 2.4 *GUI of FEAFAA batch run post-processing utility.*

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CHAPTER 3. ANN BASED PAVEMENT FOUNDATION RESPONSE PREDICTION MODELS FOR AIRCRAFT LOADS

Description of model development

Each rigid airfield pavement foundation sublayer has critical pavement responses that must be calculated. Figure 3.1 depicts some of these critical pavement responses for each type of rigid airfield pavement foundation sublayer.

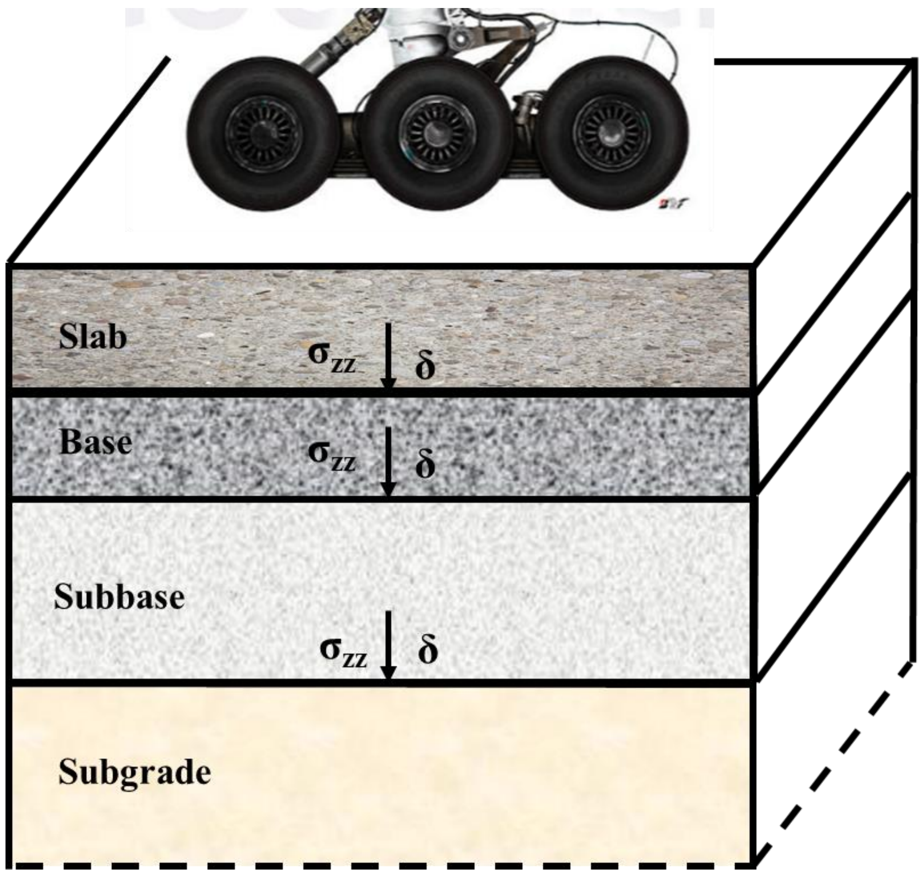

Figure 3.1 *Some critical pavement responses for rigid airfield pavement foundation sublayers.*

Separate ANN models were developed to predict each critical pavement response in each pavement foundation sublayer. ANN models were developed for two wide body aircraft loading cases: A Boeing B777-300ER and an Airbus A380-800.

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The Boeing B777-300ER has a gross weight of 352.4 metric tons (777,000 lb.) with two main gears. Each gear has a dual-tridem configuration with six wheels. Its loading on the pavement sections is a 27.9 metric tons (61,513 lb.) wheel load, approximated as a uniform pressure of 1,524 kPa (221 psi), and applied over six 0.18 m^2 (278 in^2) rectangular areas. These areas were placed at a two-axle spacing of 1.5 m. (58 in.) and a dual spacing of 1.4 m. (55 in.).

The other load, representing the A380-800, had a gross weight of 562 metric tons (1,239,000 lb.) with two six-wheel main gears. Each gear has a dual-tridem configuration with six wheels. Its loading on the pavement sections is a 44.5 tons (98,087 lb.) wheel load, approximated as a uniform pressure of 1,379 kPa (200 psi), and applied over six rectangular areas. These areas were positioned at a two-axle spacing of 1.7 m. (67 in.) and a dual spacing of 1.3 m. (53 in.).

Because of symmetry, only one of the two main aircraft gears required analysis. Nine slabs with varying slab dimensions (Lx, and Ly), loading angle (θ_g) and gear locations (x_g and y_g), were also used in the analysis.

Concrete pavement slabs typically experience curling on a daily basis because of surface warming and cooling cycles. Such a temperature effect can be simulated in the finite element model by providing an equivalent temperature gradient parameter. To account for temperature variations within the slab depth, the concept of equivalent temperature gradient (ETG) is used in FEAFAA, with ETG defined as the temperature difference between the top and the bottom of the slab per unit of slab thickness. Therefore, simultaneous mechanical and thermal loading was applied in this case.

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A total of 500 samples were used in the ANN model development (350 for training, 75 for testing, and 75 for validation, respectively). ANN model predictions for critical pavement responses in each pavement foundation sublayer for both the B777-300ER and A380-800 cases were produced and compared with the FEM solutions. Figure 3.2 shows the ANN network architecture used in the model development. The 16-40-1 (number of inputs, number of hidden neurons, and number of outputs, respectively) network architecture contains sixteen input parameters, a hidden layer composed of forty neurons, and the maximum pavement response as an output layer. This ANN architecture was selected based on its demonstrated success in previous studies with similar numbers of input and output layers for analyzing pavement systems under mechanical and thermal loadings (Gopalakrishnan et al. 2006).

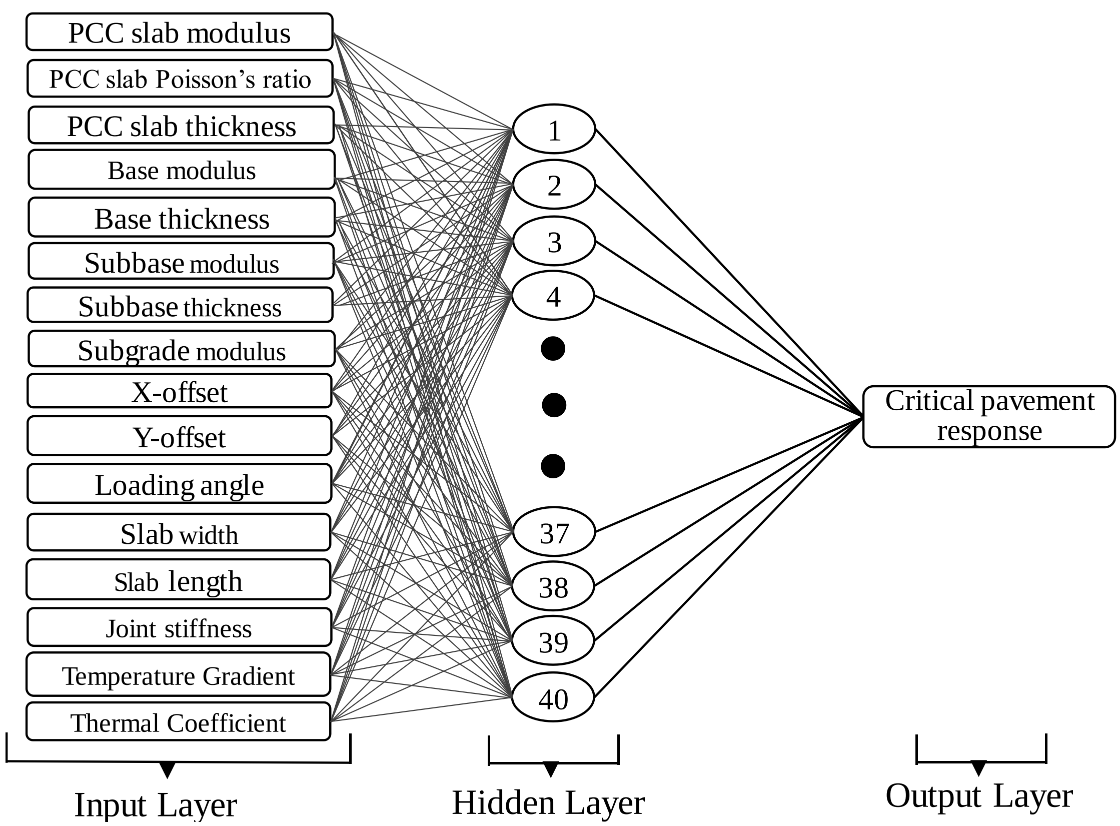

Figure 3.2 *ANN model architecture.*

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Results and Discussion

Vertical stress and deflection at top of the base layer

One of the main assumptions used in the Westergard design equations is that the vertical stress providing support to the PCC pavement is directly proportional to the vertical deflection of the slab. The strength of the rigid pavement foundation is measured by the modulus of subgrade reaction (known as the k-value). Providing a base or a subbase layer may generate better support for the subgrade, stronger support to the PCC slabs, and a higher composite k-value.

Figure 3.3 presents pavement response comparisons between the NIKE3D solutions and the ANN model predictions for maximum vertical compressive stress (σ_{zz}) at top of the base layer for (a) B777-300ER and (b) A380-800 loading. In the ANN model development, 350, 75, and 75 cases, respectively, were used for training, testing, and validation purposes.

The ANN models were found to successfully replicate FEAFAA/NIKE3D pavement response solutions in all cases. It is also important to note that validation and test sets produced a high degree of accuracy similar to that of the training set for all pavement response types, confirming ANN models' success in generalization (i.e., they did not memorize the relationship between the input parameters and output variables), and showing them to be robust and valid.

The high accuracy of the ANN model for the both aircraft types in predicting the vertical stresses at top of the base is clearly shown in Figure 3.3. The ANN models predicted maximum σ_{zz} at top of the base with a great accuracy with correlation coefficient (R^2) of 0.999. The average of the squares of the errors between the ANN model and the NIKE3D finite-element solution results for both aircraft are quite low (42 and 70 for B777-300ER and A380-800 respectively), showing that the quality of the ANN model prediction is very

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acceptable. As can be easily seen from Figure 3.3, vertical stress at top of the base is higher under the A380-800 gear load than under the B777-300ER load. The A380-800 has 562 metric tons (1,239,000 lb.) gross weight with 95 percent of its weight on the main gears. The B777-300ER has a 352 metric tons (777,000 lb.) gross weight with 95 percent of its weight on the main gears. Figure 3.3 shows a higher range of vertical stresses at top of the base for a heavier gear load of A380-800.

Figure 3.4 shows maximum vertical deflection predictions by the ANN model and NIKE3D solutions for (a) the B777-300ER and (b) the A380-800 gear loadings. The well-trained ANN model results for vertical deflection at top of the base are presented in the figure, with correlation coefficient values (R^2) of 0.999 for both aircraft loadings and a very low Mean Squared Error (MSE) of 5.03E-04 and 8.34E-04 for B777 and A380, respectively. Similar to the vertical stresses, vertical deflections are higher for the A380-800 load than the B777-300ER load.

Vertical stress and deflection at top of the subbase layer

A comparison between the ANN-predicted maximum vertical stresses values at top of the subbase and those obtained using the NIKE3D are shown in Figure 3.5. As shown in this figure, almost all 500 ANN predictions fell on the line of equality for the two types of airplane gear loads, indicating both proper training and excellent prediction performance of the ANN models. The correlation coefficient for the maximum vertical stress at top of the subbase for both values of aircraft loading was 0.999.

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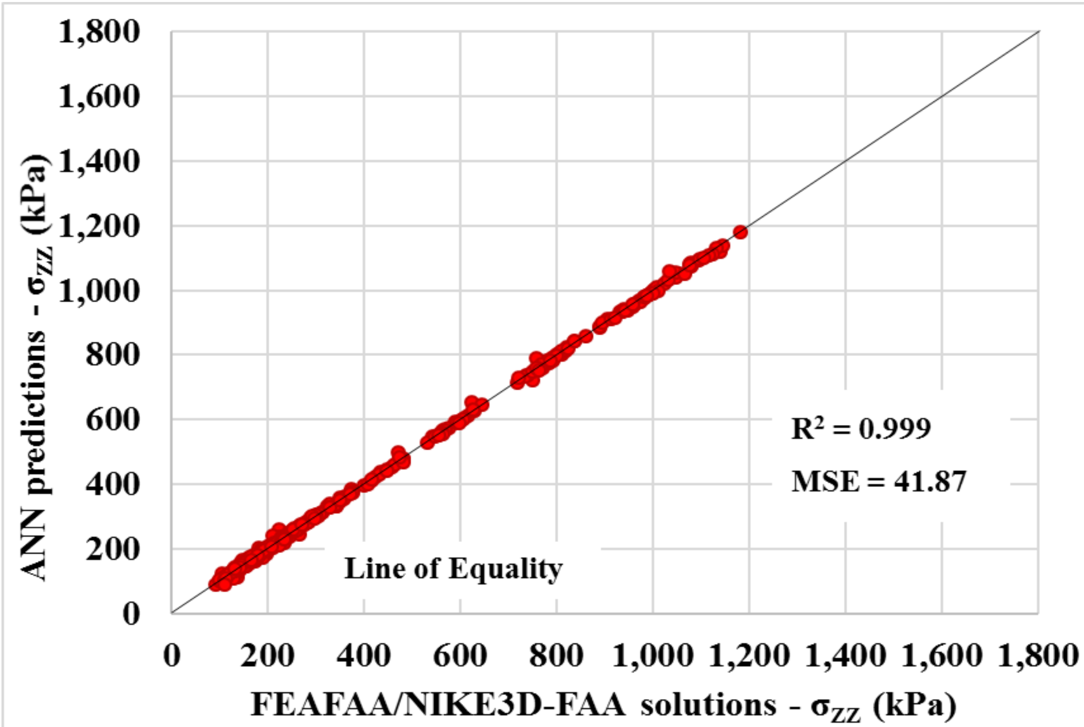
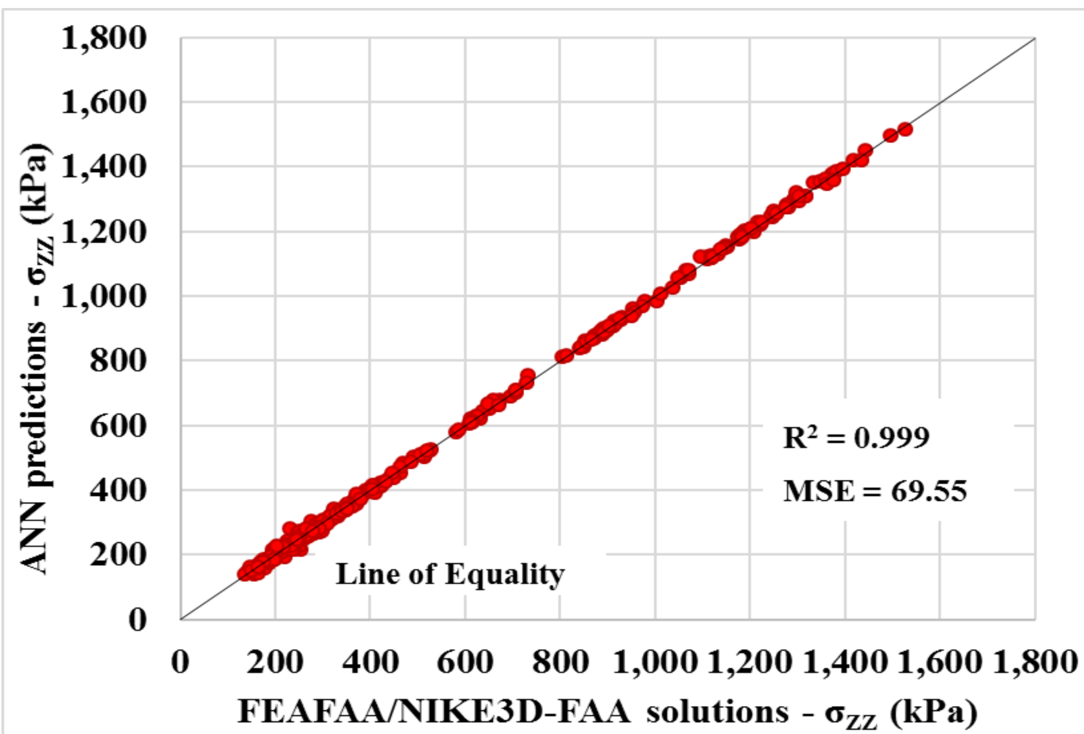


(a)



(b)

Figure 3.3 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical compressive stress (σ_{ZZ}) at top of the base for (a) B777-300ER (b) A380-800 gear loadings.*

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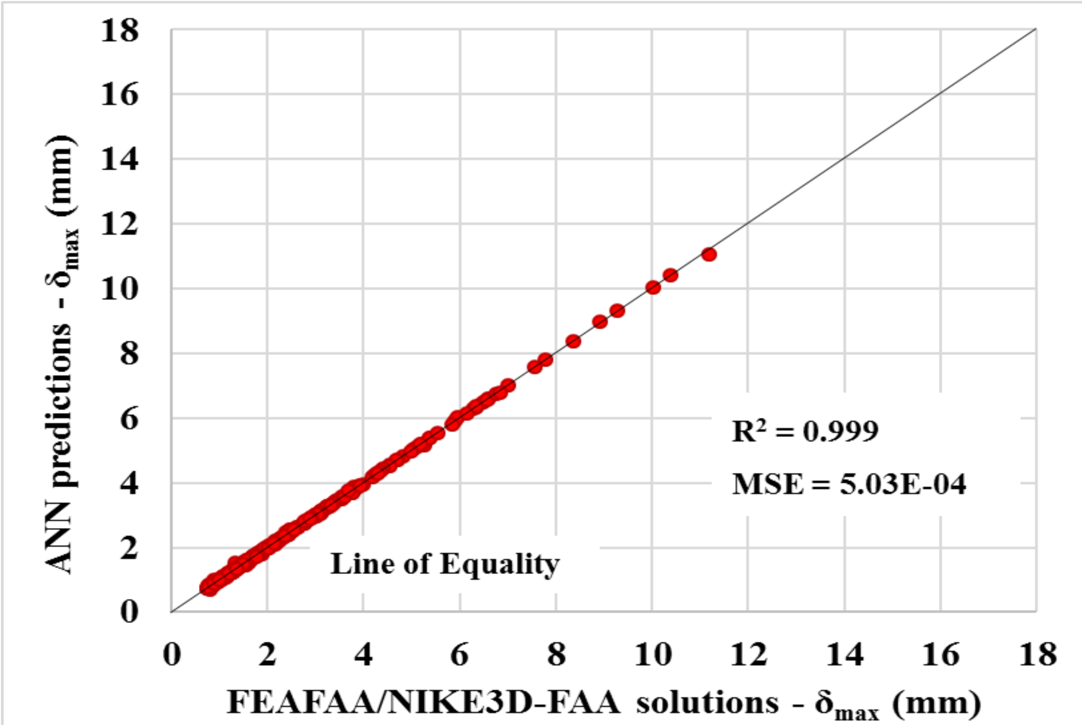
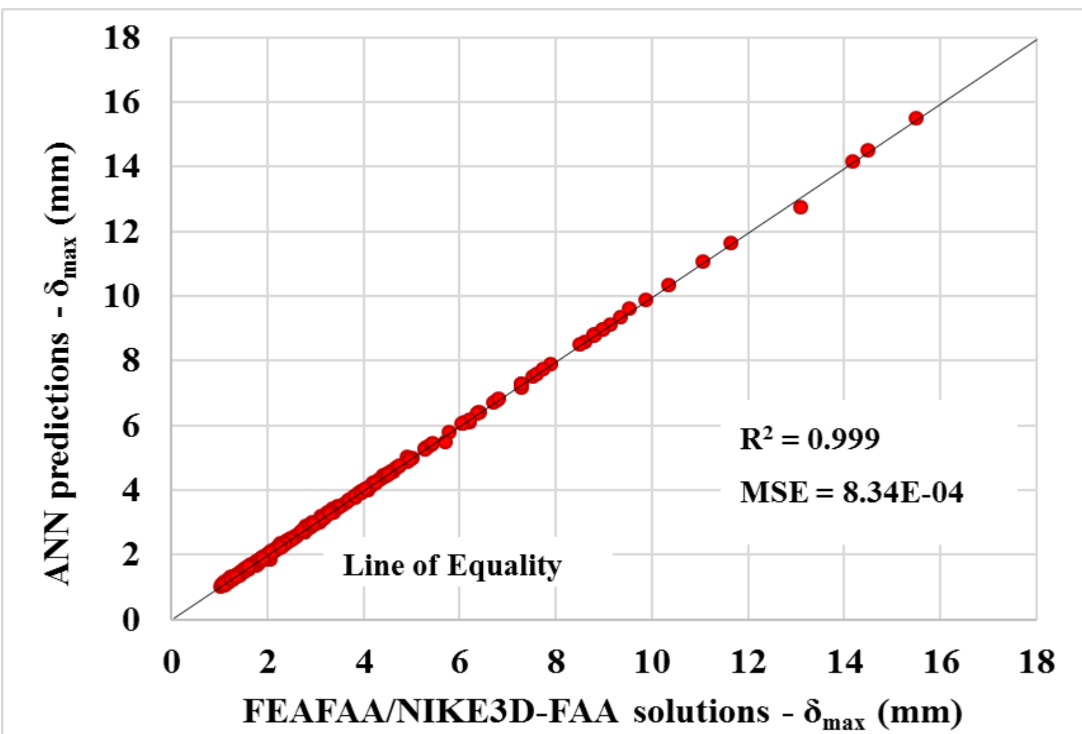


(a)



(b)

Figure 3.4 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical deflection (δ) at top of the base for (a) B777-300ER (b) A380-800 gear loadings.*

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The MSE, showing the average square errors, was 13.09 and 12.76 for the Boeing and the Airbus aircraft loadings, respectively. In other words, the average of the difference between ANN-predicted values and NIKE3D solutions are the square root of MSEs, almost 3.6 kPa for both aircraft types. This reflects very little difference between ANN-predicted values and NIKE3D solutions, showing that the predicted results are highly reliable and accurate.

Figure 3.5 depicts that the maximum vertical stresses at top of the subbase is higher when the A380-8800 gear load is applied. The maximum stresses at top of the subbase for a varied set of 500 inputs sets ranged from almost 80 kPa to 600 kPa for a pavement structure subjected to the B777-300ER gear load, and from 100 kPa to almost 800 kPa for a pavement structure subjected to the A380-800 gear loading.

Separate ANN models were trained to predict the maximum vertical deflections at top of pavement structures subjected to B777-300ER and A380-800 gear loadings. Figure 3.6 shows a comparison between ANN-predicted values and NIKE3D solutions for maximum deflection at top of the subbase. Good performance of the highly-accurate and well-trained ANN model is noticeable in Figure 3.6 that shows that the predicted values either fell on the line of equality or are very close to that line. High correlation coefficients (higher than 0.999) and very low MSE values demonstrate the very high accuracy of the model.

Figure 3.6 also indicates that maximum vertical deflections at top of the subbase is higher when the A380-800 gear load is applied. The range of maximum vertical deflections at top of the subbase for many of input sets ranges from almost 0.5 mm. to less than 12 mm. for a pavement structure subjected to the B777-300ER gear load, and from 1 mm. to almost 16 mm. for a pavement structure subjected to the A380-800 gear load.

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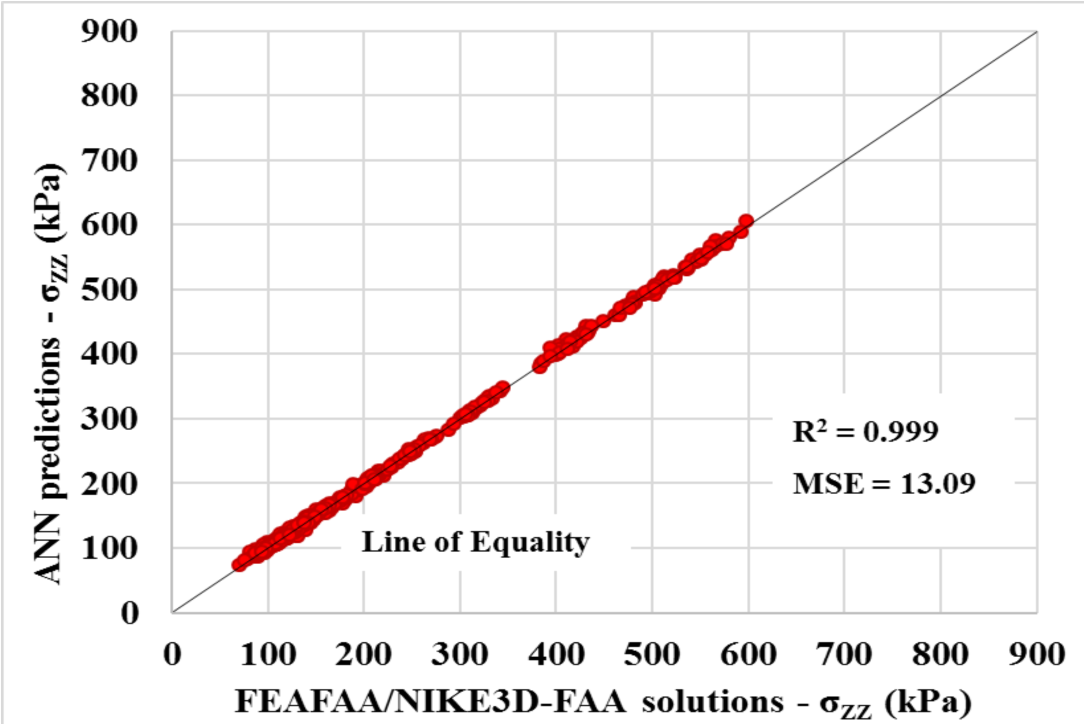

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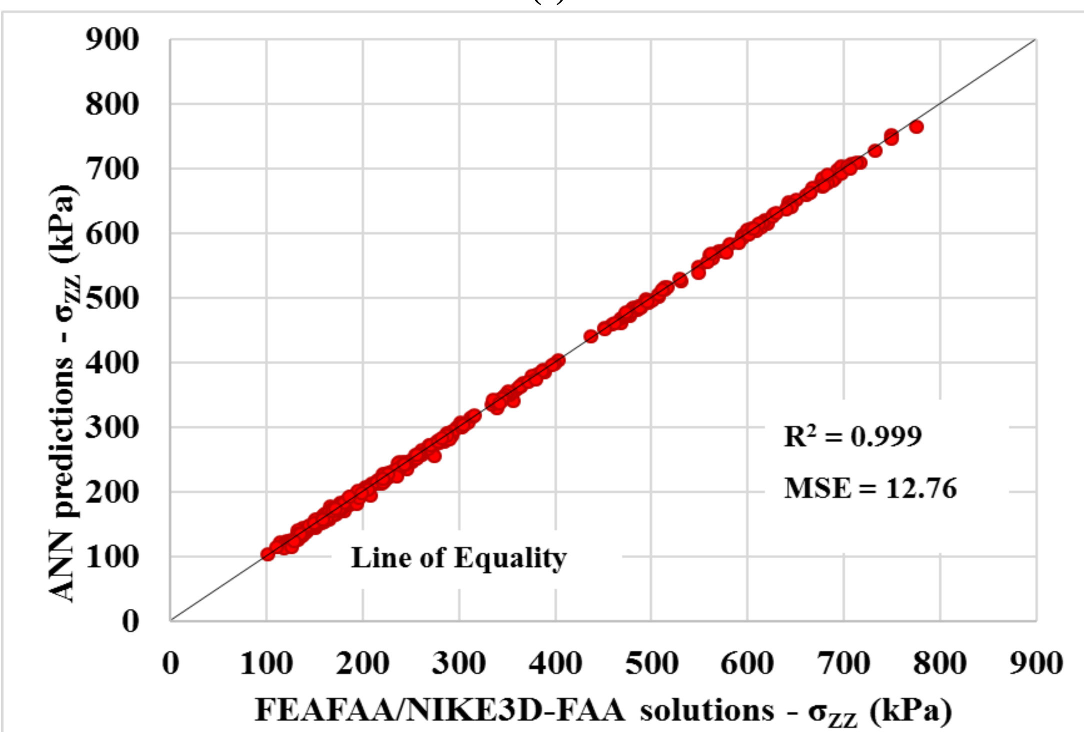

(b)

Figure 3.5 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical compressive stress (σ_{ZZ}) at top of the subbase for (a) B777-300ER (b) A380-800 gear loadings.*

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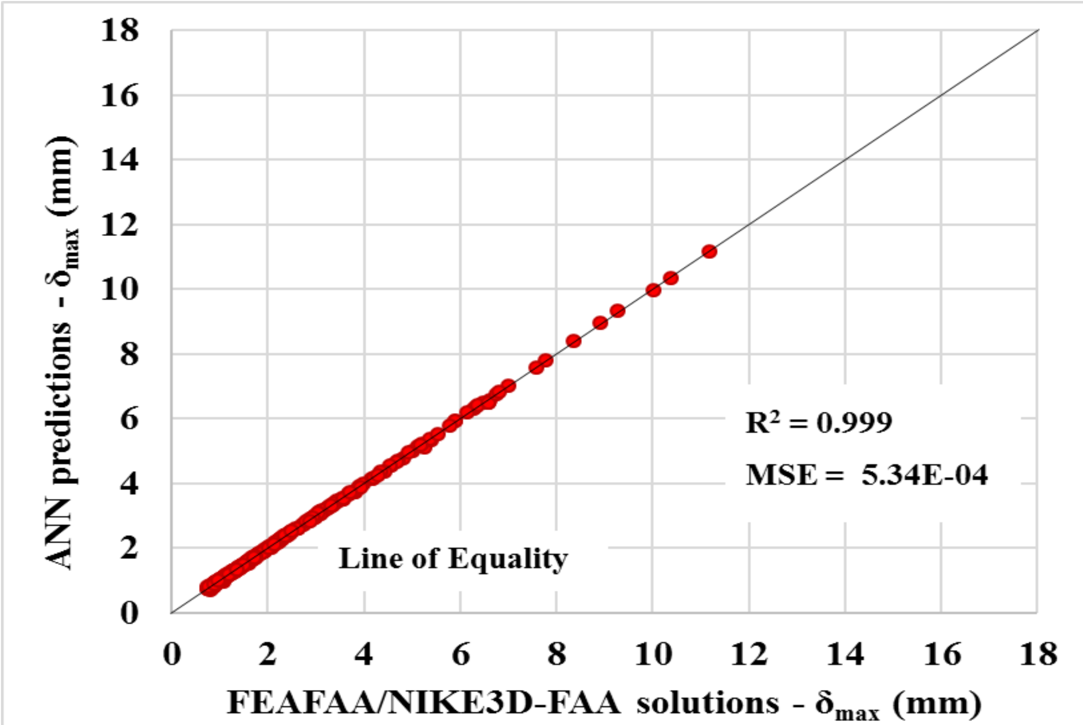

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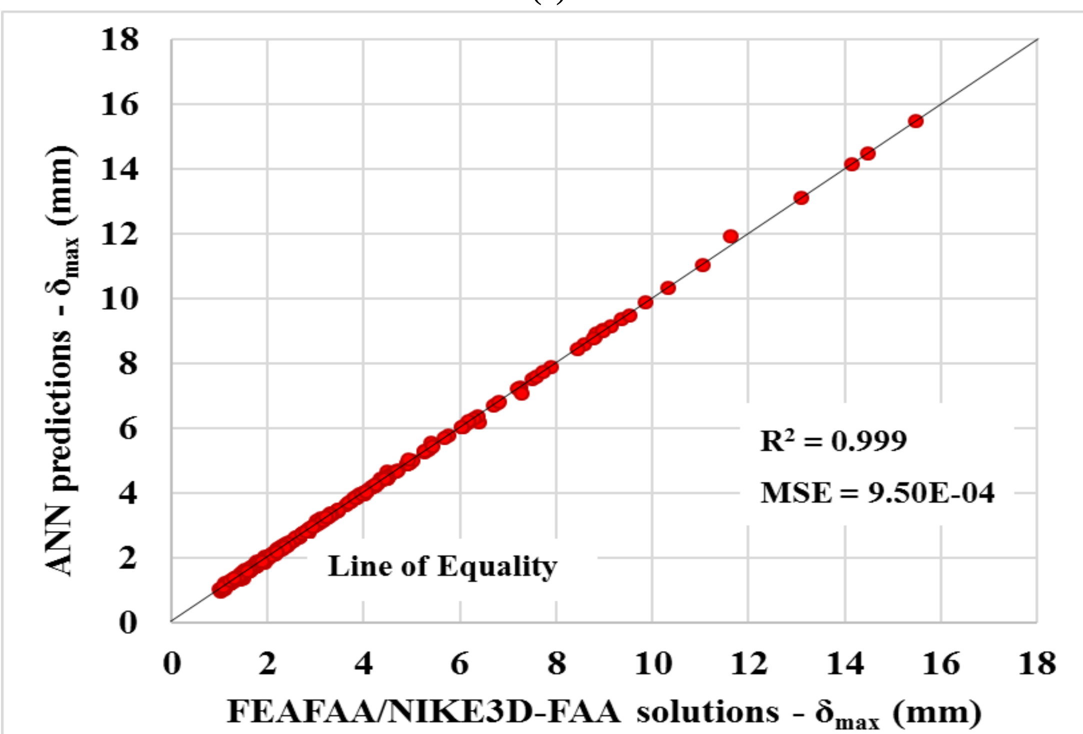

(b)

Figure 3.6 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical deflection (δ) at top of the subbase for (a) B777-300ER (b) A380-800 gear loadings.*

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Vertical Stress and Deflection at Top of the Subgrade

Figure 3.7 illustrates pavement response comparisons between the NIKE3D solutions and the ANN model predictions for vertical compressive stresses at top of the subgrade for (a) B777-300ER and (b) A380-800. The high accuracy of the ANN model for both aircraft in predicting the vertical stresses at top of the subgrade is clearly represented by a high correlation coefficient and low MSE values as shown in Figure 3.7.

The ANN models predicted a maximum σ_{zz} at top of the subgrade with greater than 0.999 correlation coefficient accuracy. The average square errors between ANN model predictions and NIKE3D solution results for both aircraft are relatively very low, as 1.06 for B777-300ER and 0.99 for A380-800 gear loadings.

NIKE3D solutions for the B777-300ER and the A380-800. High correlation coefficient, very low MSE, and results with very good fit to the equality line show that the ANN model was very well-trained and can estimate the maximum vertical deflections at top of the subgrade with great accuracy.

By comparing Figure 3.4, Figure 3.6, and Figure 3.8 it can be concluded that the main deflection occurs at top of the subgrade, with the base and subbase layers having very low deflections. This reflects the importance of the subgrade deflection with respect to overall deflection of a rigid pavement structure.

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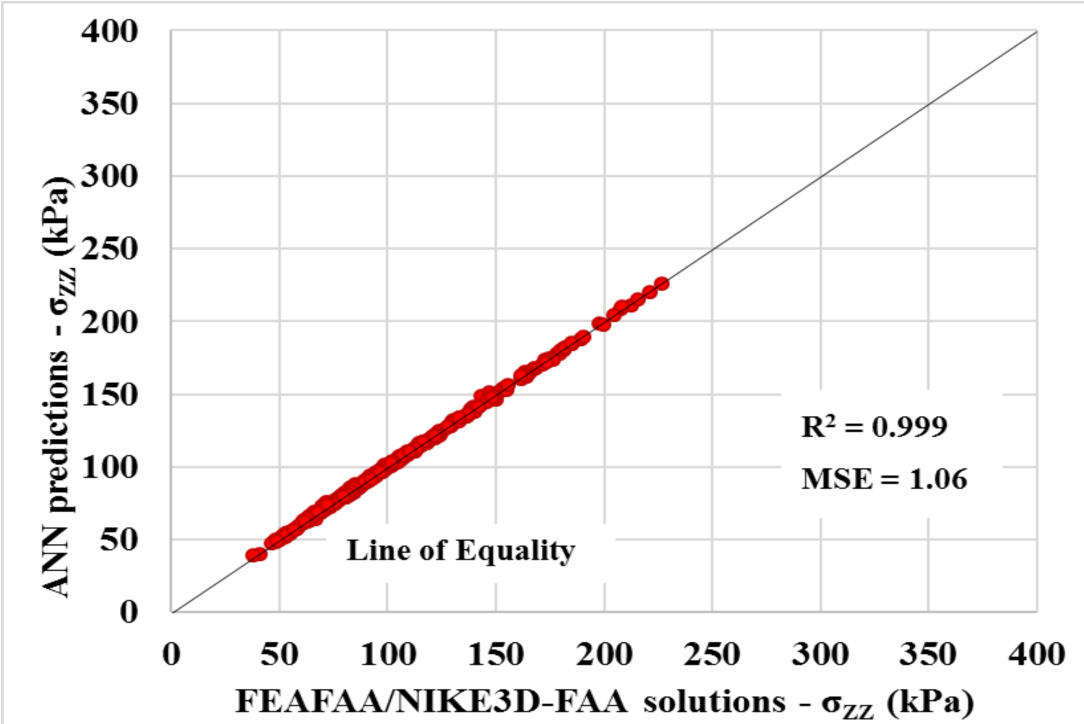

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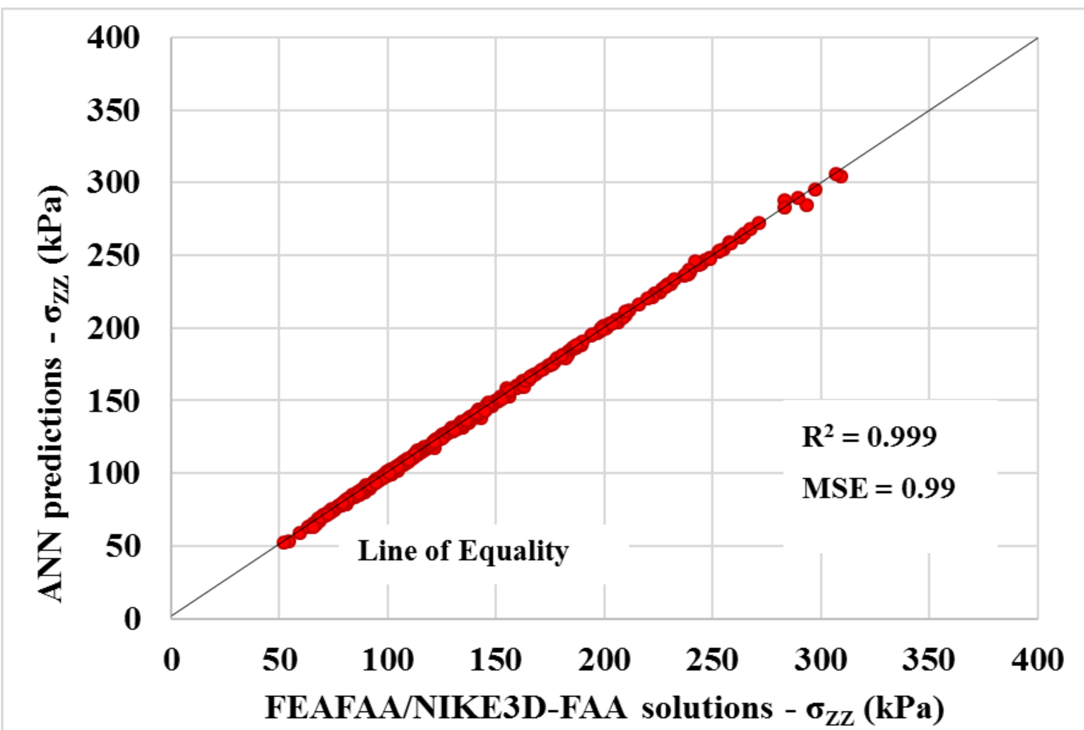

(b)

Figure 3.7 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical compressive stress (σ_{ZZ}) at top of the subgrade for (a) B777-300ER (b) A380-800 gear loadings.*

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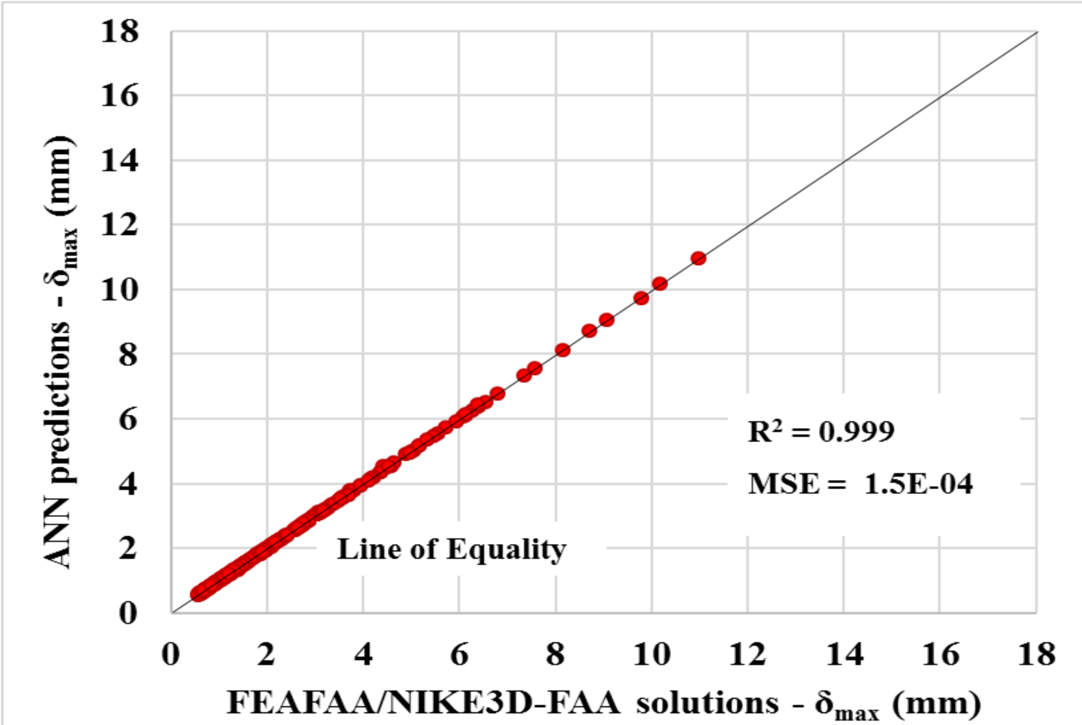

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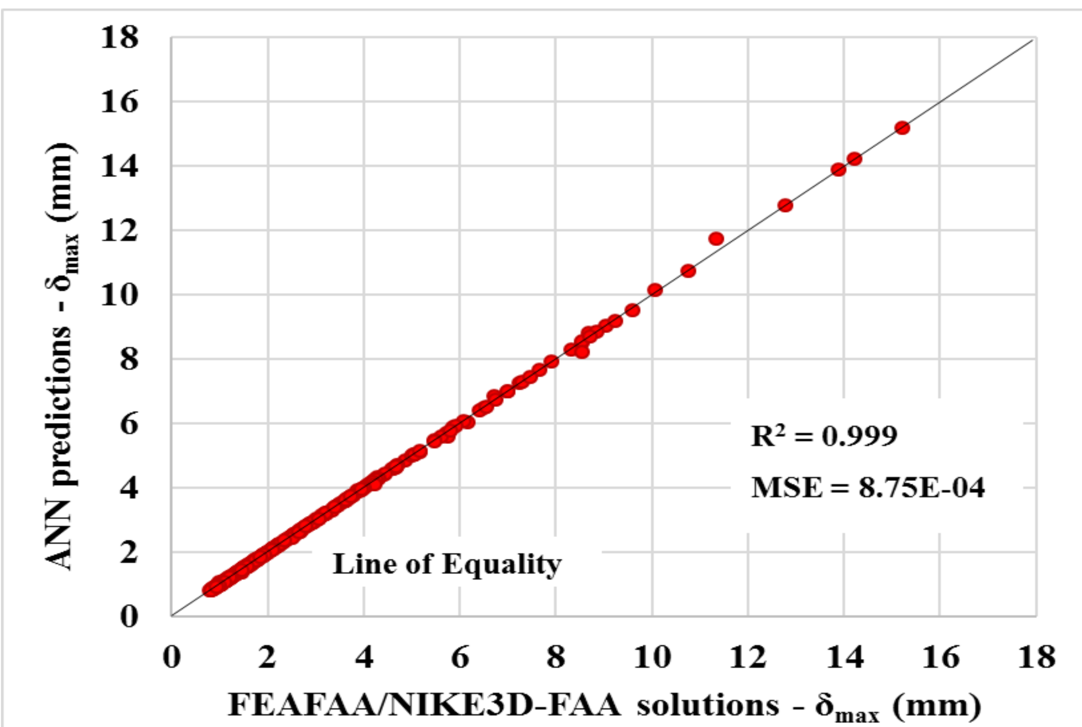

(b)

Figure 3.8 *ANN model response predictions vs. NIKE3D finite element solutions for maximum vertical deflection (δ) at top of the subgrade for (a) B777-300ER (b) A380-800 gear loadings.*

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CHAPTER 4. ANN BASED PAVEMENT FOUNDATION RESPONSE PREDICTION MODELS FOR HWD/FWD LOADS

Description of model development

FEAFAA software lets a user add new aircraft and any generic single and dual-wheel configurations to its library along with other aircraft parameters. To simulate FWD/HWD testing in FEAFAA, a generic single wheel loading was introduced, with a 16.3 metric tons (36,000 lb.) applied load, with a square footprint of 304.8×304.8 mm. (12×12 in.), producing a tire pressure of 1,724 kPa (250 psi). This generic single wheel was added to the library of FEAFAA as HWD plate loading, which was applied at the center of the slab.

Similar to the previous procedure, a synthetic database comprised of 500 samples was developed for various slab and pavement foundation sublayer thicknesses and moduli values. In this case, only a mechanical load was applied to the pavement system. The ranges of used FEAFAA inputs were given the same values as in the previous case (Figure 3.2) but without any thermal loading inputs.

FEAFAA runs using the automation tool were performed 500 times for all these cases. The automation tool was modified to extract deflections in theoretical radial offset distance from the FEAFAA output files, and computed slab deflections were extracted, as well as all pavement foundation sublayers under the theoretical radial offset distances were automatically located in the finite element based knowledge database (see Figure 4.1). Figure 4.2 shows the applied load and theoretical radial offset distances as well as the deflections. The locations of selected radial offsets were 0 mm., 305 mm. (12 in.), 610 mm. (24 in.), 914 mm. (36 in.), 1,219 mm. (48 in.), and 1,524 mm. (60 in.) from the center of the load to simulate the actual HWD loadings on the pavement system.

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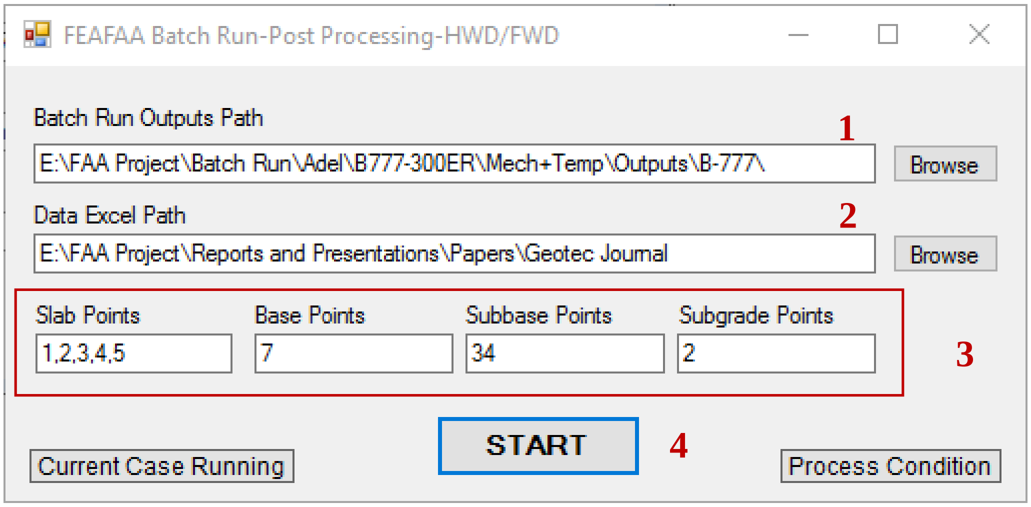

1. Directory of output files generated by NIKEPLOT
2. Directory of datasets spreadsheet
3. Analysis points' identification numbers
4. Start post-processing

Figure 4.1 *GUI of FEAFAA batch run post-processing utility for HWD/FWD loading.*

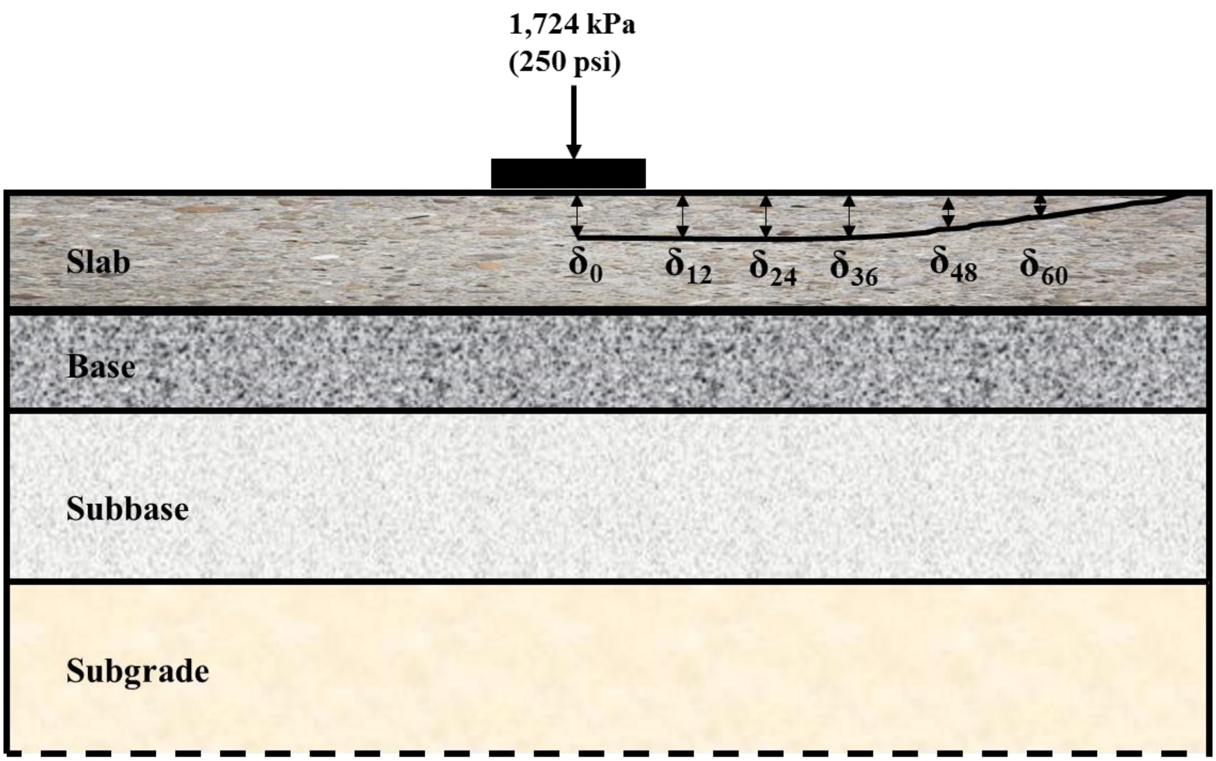

Figure 4.2 *Load and theoretical radial offset distances in simulation of HWD testing.*

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An ANN model was developed to predict deflections under theoretical radial offset distances for the slab and each of the pavement foundation sublayers. In the ANN model development, all the various FEAFAA input parameters were provided as inputs and computed deflections were taken as outputs. Figure 4.3 shows the ANN network architecture used in the model development: fourteen input parameters, a hidden layer composed of forty neurons, and six deflection values as an output layer.

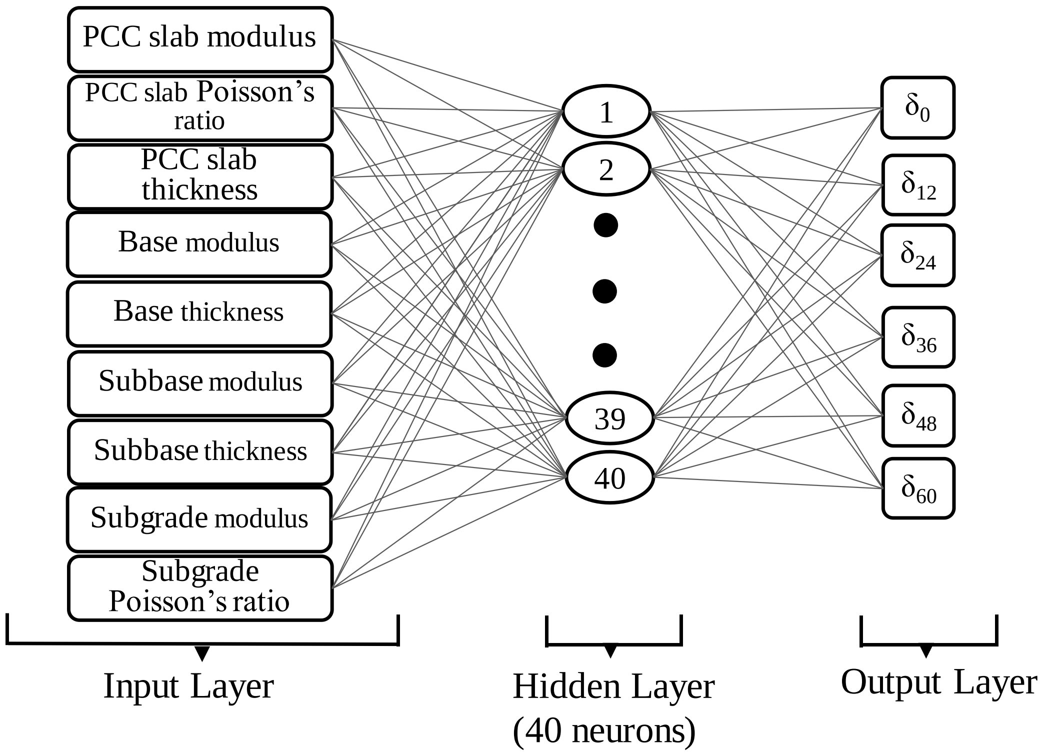

Figure 4.3 *ANN network architecture used in the model development.*

Results and Discussion

Separate ANN models were trained to predict the deflection of each pavement sublayer. Each ANN model was trained for one pavement sublayer, estimating deflections on that layer at the locations of radial offsets (0 mm., 305 mm. (12 in.), 610 mm. (24 in.), 914 mm. (36 in., 1,219 mm. (48 in.), and 1,524 mm. (60 in.)).

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Figure 4.4 provides comparisons between the NIKE3D solutions and the ANN model predictions of the deflections at the selected points for each pavement layer. Figure 4.4 clearly shows that the developed ANN models predict deflections at radial offsets for each layer with high accuracy. Figure 4.4 (a) shows ANN predicted deflections at top of the slab vs. NIKE3D solutions. The deflection at top of the slab is the overall deflection, the sum of deflections of all layers. The developed ANN model predicted the NIKE3D results of overall deflections at the six points by nearly 1.00 correlation coefficient accuracy.

The deflection at top of the base is actually the overall deflection of the pavement's foundation. Figure 4.4 (b) displays the ANN model prediction vs. NIKE3D results for the selected points at top of the base. The ANN model's high accuracy is represented by correlation coefficient of 0.999 and a very low MSE value of 1.8E-05. In other words, the overall pavement foundation deflections at different points were accurately predicted by the ANN model.

Figure 4.4 (c) depicts the capability of the ANN model for predicting the deflections at top of the subbase. The correlation coefficient value obtained was 0.999 and the average square error was 2.3E-05, reflecting very low error and high accuracy. ANN model estimation results for the deflection at top of the subgrade are presented in Figure 4.4 (d). As for other layers, the deflections at top of the subgrade were accurately predicted by the ANN model with a correlation coefficient of 1.00 and an average square error of 7.5E-06. The capability of the ANN model developed in this study to predict surface deflection is high at all offsets. Note that, while the magnitude of HWD surface deflections decreases with increasing radial offset, for the ANN developed models in this study, the prediction accuracy would not decrease as radial offset increases.

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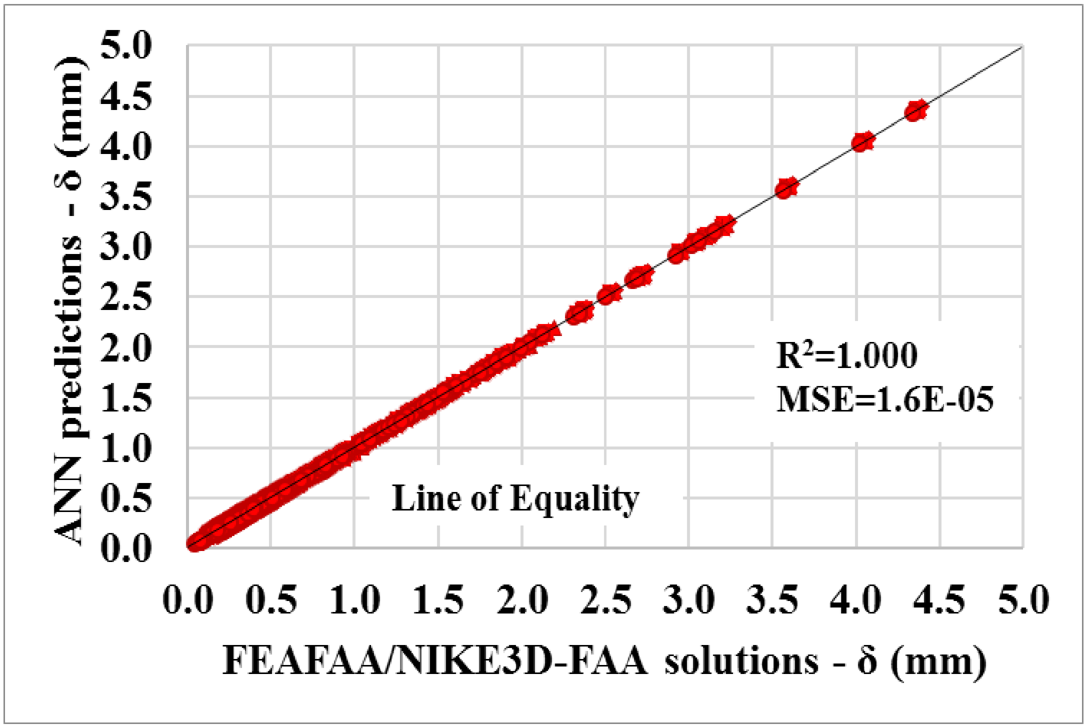

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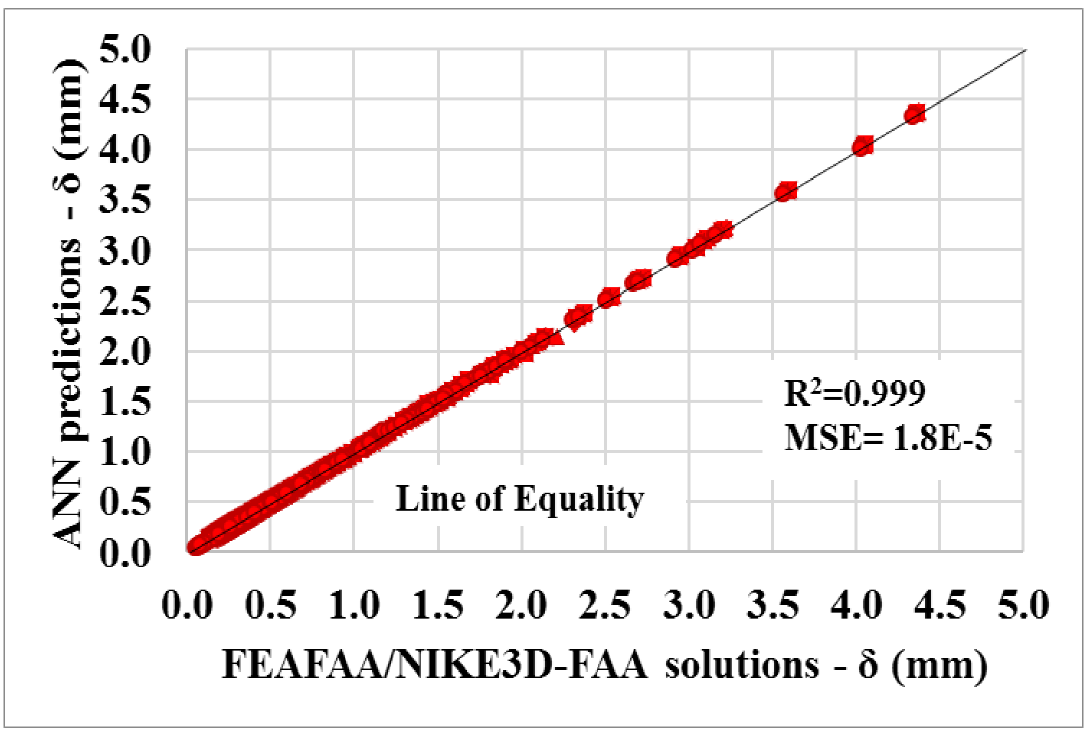

(b)

Figure 4.4 *ANN pavement foundation response predictions for HWD/FWD loads vs. NIKE3D finite element solutions for vertical deflections (δ) at top of the (a) PCC slab, (b) base, (c) subbase, (d) subgrade.*

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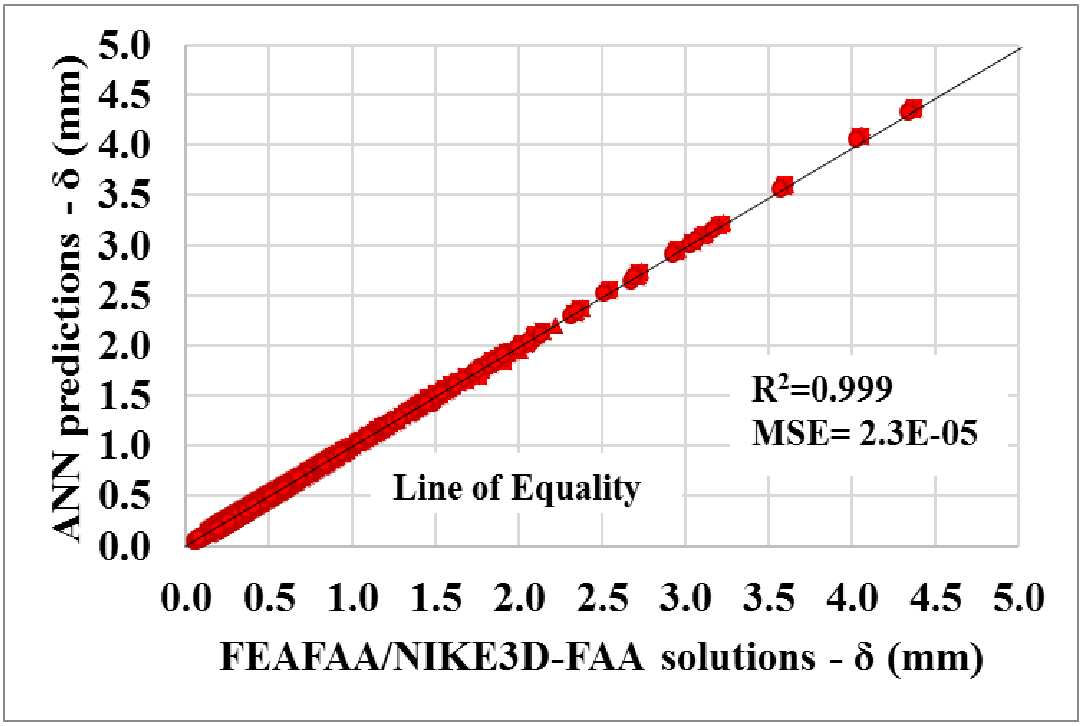

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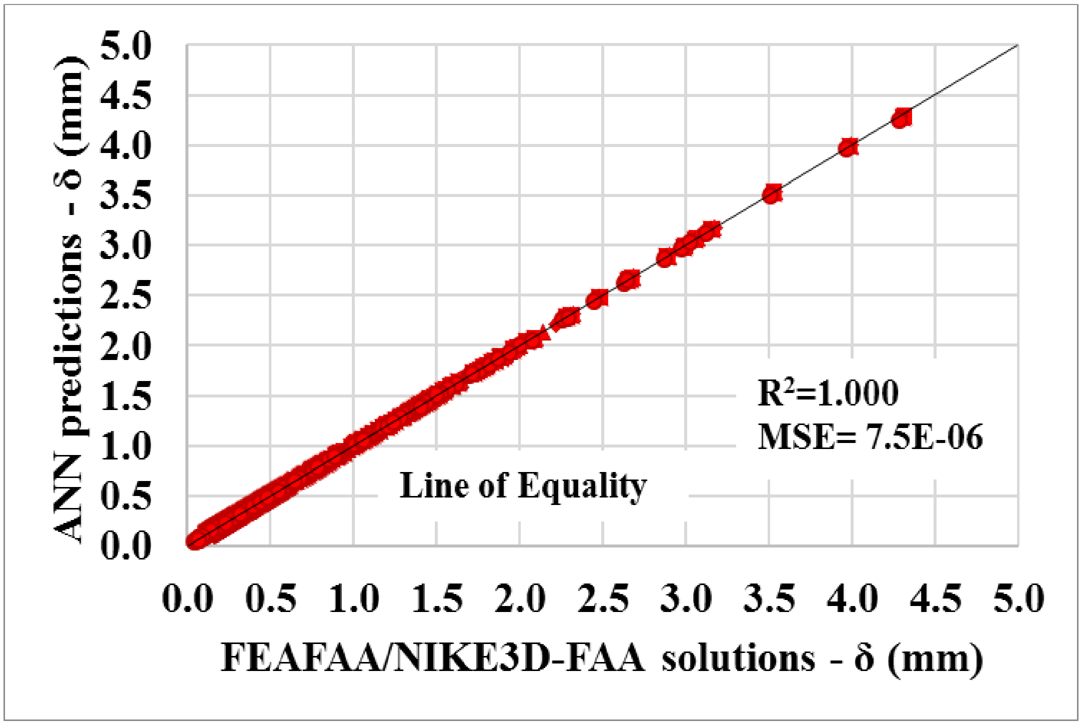

(d)

Figure 4.4 (continued)

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CHAPTER 5. ANN BASED SINGLE RIGID-PAVEMENT MODULI PREDICTION MODEL FOR HWD/FWD LOADS

Description of model development

In this study, a 16-40-4 (sixteen inputs, one hidden layer with 40 hidden neurons each, and four outputs) architecture was used for developing the ANN models. The best training ANN model among 10 different trainings was chosen based on its highest value of correlation coefficient. The ANN model was trained for 500 different cases. The objective is to backcalculate the elastic modulus values for the pavement layers. The deflection data, including the six HWD/FWD surface deflections calculated by NIKE3D at (0), and at radial offsets of 254 mm. (12 in.), 610 mm. (24 in.), 914 mm. (36 in.), 1,219 mm. (48 in.), and 1,524 mm. (60 in.), were added to the inputs. The ANN model architecture is shown in Figure 5.1.

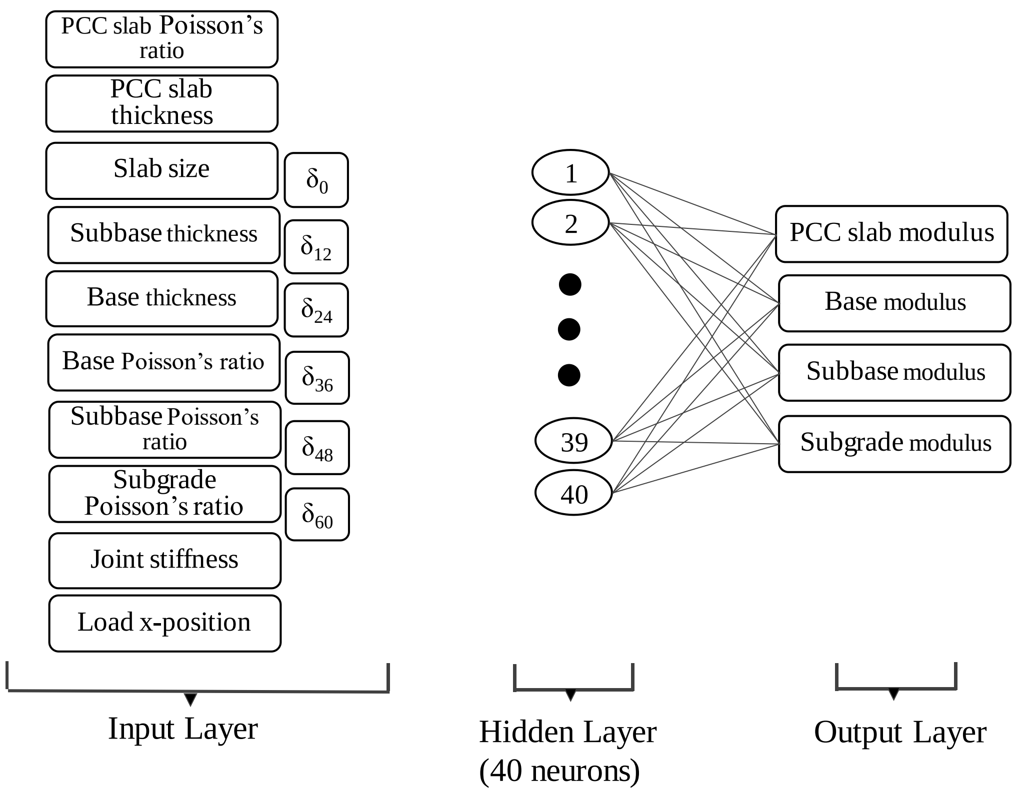

Figure 5.1 *ANN network architecture used in the backcalculation model development.*

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Results and Discussion

An ANN model to backcalculate the elastic modulus of all layers was developed. Figure 5.2 presents the prediction performance of the ANN backcalculation model in predicting the elastic modulus of each layer separately. The predicted elastic modulus values for the slab are depicted in Figure 5.2 (a). As shown in this figure, almost all 500 ANN predictions fell on the line of equality, indicating proper training and excellent performance of the ANN models. The correlation coefficient value of 1.00 reflects very high accuracy with MSE of 5.2E-06 whose square root reflects the average error of the model, so the average error of the ANN predictions is 2.3E-03 GPa, a very low value related to the range of elastic modulus values (20 to 50 GPa).

Figure 5.2 (b) shows the predicted elastic moduli values of the base layer vs. moduli used in NIKE3D runs. This figure also shows that all ANN predictions for the 500 cases fall on the line of equality, reflecting accurate and exceptional performance of the ANN backcalculation model.

The performance of the ANN backcalculation model in predicting the subbase modulus is shown in Figure 5.2 (c). The figure indicates that, while the accuracy of the model in estimating the subbase modulus is not as high as the accuracy of the model in predicting the modulus values of the slab and the base layer, the performance of the ANN backcalculation model is acceptable in predicting the subbase modulus. The ANN model can predict the modulus of the subbase with 0.938 correlation coefficient accuracy and a MSE of 6.5E-04, i.e., actually an average error of 2.5E-02 GPa, relatively low for the range of subbase modulus values (higher than 0.1 GPa).

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The backcalculated elastic subgrade modulus values are displayed in Figure 5.2 (d). The figure reflects the appropriate performance of the ANN backcalculation model in predicting the modulus of the subgrade with correlation coefficient of 0.997. Overall, Figure 5.2 thus reflects the very reliable results produced by using just one ANN backcalculation model to predict the modulus values of all layers of the rigid pavement.

A major benefit of applying the developed ANN backcalculation model in routine HWD/FWD evaluations results from the high-speed data processing and analyses that can even be performed in the field on a real-time basis.

The ANN models developed in this study are orders of magnitude faster than the NIKE3D solutions, and they do not require lengthy and detailed finite-element pre- and post-processing tasks. In addition, the ANN models do not require assumed initial layer moduli (i.e., seed moduli) that can be difficult to determine if a user for BAKFAA is unsure what modulus value to expect for each layer.

The rapid prediction ability of the ANN backcalculation models makes them perfect tools for analyzing the FWD deflection data, thereby assessing the condition of pavement section in real time during field tests.

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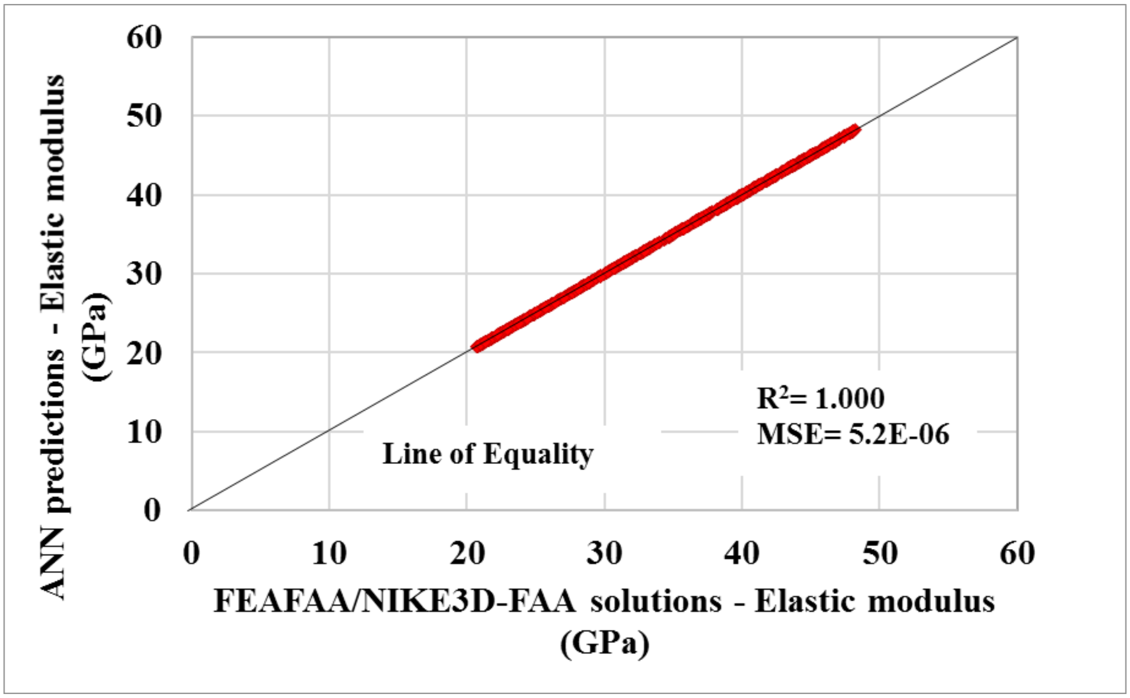

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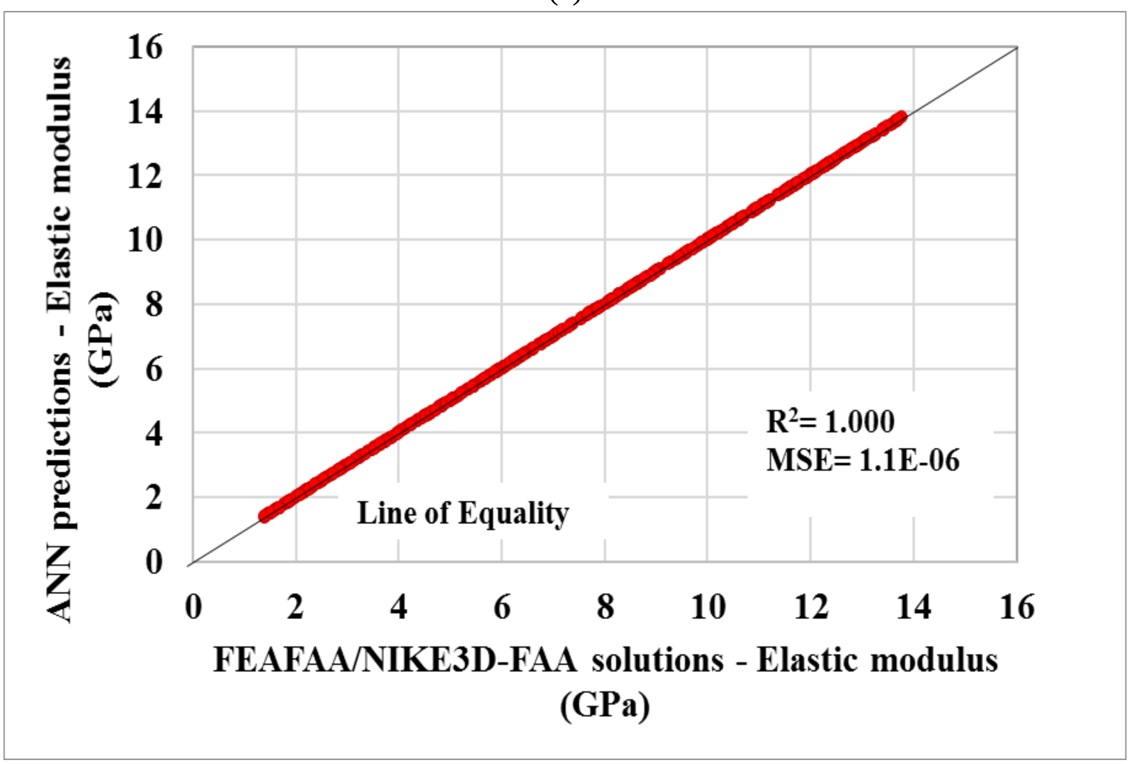

(b)

Figure 5.2 *ANN pavement moduli predictions for HWD/FWD loads vs. NIKE3D finite element results for elastic modulus of the (a) PCC slab (b) base (c) subbase (d) subgrade.*

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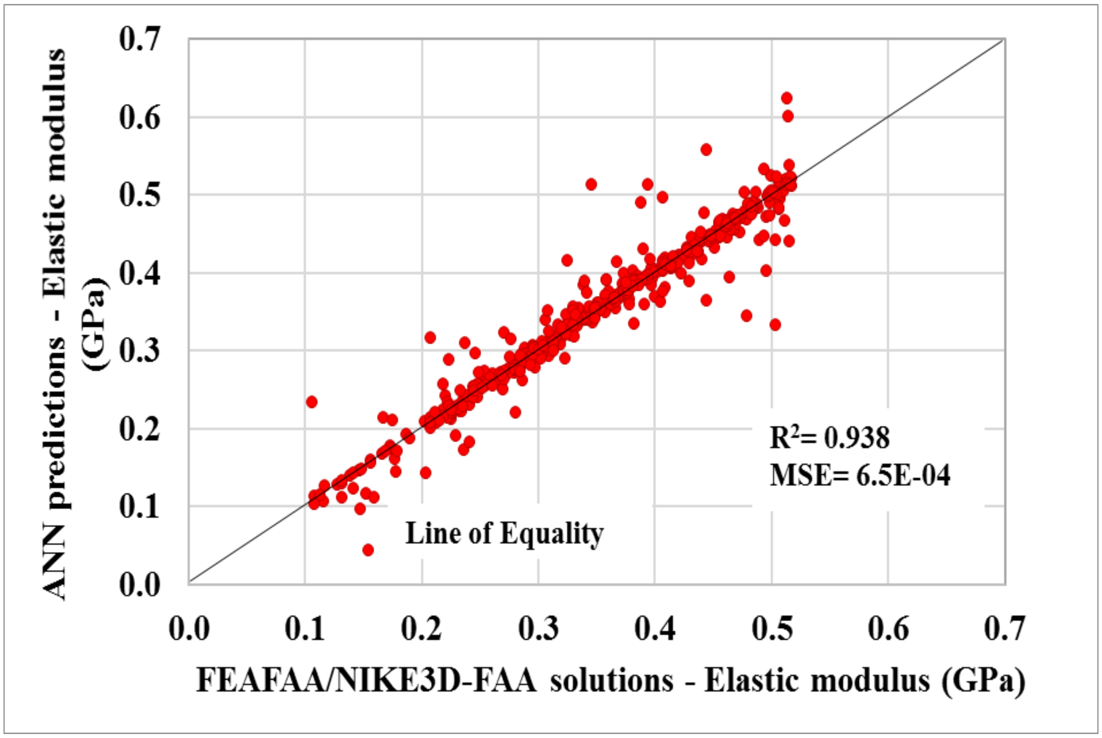

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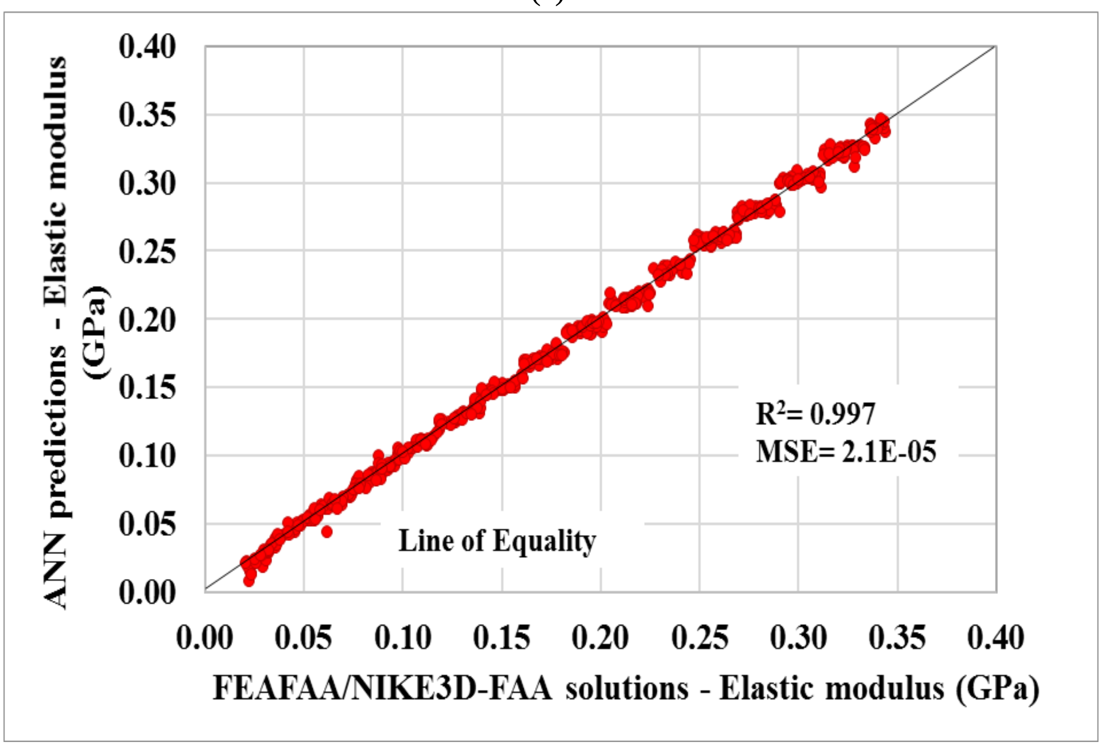

(d)

Figure 5.2 (continued)

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CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The primary objective of this study is to investigate the feasibility of developing rapid three-dimensional finite-element (3D-FE)-based pavement foundation response and moduli prediction models for design of both new and rehabilitated rigid airfield pavement structures. The three model types developed in this study include: (1) rigid-pavement foundation response prediction models for different aircraft loading conditions, (2) rigid-pavement foundation response prediction models for HWD/FWD loading conditions, and (3) single rigid pavement moduli prediction model (i.e., backcalculation models).

A set of finite elements based knowledge database was created by conducting hundreds of batch runs using FEAFAA/NIKE3D tool for two aircraft, the B777-300ER and the A380-800. ANN models were developed for predicting maximum deflections and vertical stresses in pavement foundation layers (Base, Subbase, and Subgrade). The results were that the ANN models accurately predicted the vertical stresses and overall deflection at top of the foundation layers. NIKE3D batch runs were also conducted for HWD/FWD test loading, followed by ANN models developed to predict deflections at specific theoretical radial offset distances from the plate load for the slab and each pavement foundation sublayer. Results obtained in this study showed that the developed ANN models have excellent capability for predicting the deflection at any offset, and their prediction accuracy did not decrease by when the radial offset was increased.

A single ANN model was developed to backcalculate the elastic modulus of all pavement layers, and the results reflected very accurate moduli predictions for all layers. The

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major benefits of applying the developed ANN backcalculation model in routine HWD/FWD evaluations are as follows:

The ANN backcalculation model was developed based on a finite element based knowledge database created by NIKE3D, employed in FAA's pavement design software, FAARFIELD, to compute concrete pavement responses. The ANN backcalculation model is consistent with NIKE3D for design of new and rehabilitated (i.e., overlays of existing concrete pavements) rigid airfield pavement structures.

The ANN models do not require assumed initial layer moduli (i.e., seed moduli) that can be difficult to determine if a user of FAA's backcalculation software, BAKFAA, is unsure as to what modulus value to expect for each layer.

Unlike using iterative optimization techniques where the optimizer can get stuck in local minima of the solution space, ANN backcalculation models have higher likelihood of predicting near-global moduli solutions.

The use of ANN backcalculation models results in high-speed data processing and analyses that can even be performed in the field; the ANN models developed in this study are orders of magnitude faster than the NIKE3D solutions. The rapid predictive ability of the ANN backcalculation models makes them perfect tools for analyzing the HWD/FWD deflection data, and thus assessing the condition of pavement sections in real time during field tests.

Recommendations

Current airport rigid pavement design practices do not consider pavement foundation failures (settlement, erosion, etc.) which have been observed in actual airport rigid pavement during its service life. The ANN models (i.e., case 1 forward models) in this study utilized the state-of-the-art 3D FE pavement response solutions for ANN model development. Such

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ANN models could relate to actual rigid pavement foundation related distresses and associated pavement failures. Further, they could potentially be integrated into FAARFIELD as surrogate forward response prediction models for design of new and rehabilitated airfield rigid pavement systems in consideration of pavement foundation failures during service life.

The HWD load location (interior) was fixed in this study and the effects of curling and warping were not considered. For further investigation, authors recommend study of different HWD load locations on the slab (corner, mid slab edge, or random locations) and both mechanical and simultaneous mechanical and thermal loading cases. The ANN backcalculation model compatibility for predicting the critical stresses or maximum responses on the slab or even on different layers should also be studied. Future studies will also focus on extending the model further using hybrid soft computing techniques such as nature-inspired metaheuristics for inverse analysis in combination with ANN forward-modeling predictions.

To meet all objectives of such future study, the developed ANN models can be applied to field HWD/FWD data acquired at the NAPTF during full-scale traffic testing of rigid pavement sections using six-wheel and four-wheel heavy aircraft gear loading. Non-dimensional ANN backcalculation models could also be developed. An advantage of using dimensional analysis in the development of ANN models is that this significantly reduces the number of required input parameters.

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REFERENCES

Ceylan H, Tutumluer E, Barenberg EJ. Artificial Neural Networks for analyzing concrete airfield pavements serving the Boeing B-777 Aircraft. Transportation Research Record: Journal of the Transportation Research Board 1999; 1684:110–117.

Ceylan H. Analysis and Design of Concrete Pavement Systems Using Artificial Neural Networks. University of Illinois at Urbana-Champaign, Urbana, IL. 2002.

Ceylan H, Guclu A, Tutumluer E, Thompson MR. Backcalculation of full-depth asphalt pavement layer moduli considering nonlinear stress dependent subgrade behavior. International Journal on Pavement Engineering 2005;6(3):171–182.

Ceylan H, Gopalakrishnan K, Bayrak MB. Neural networks applications in transportation infrastructure systems. International Journal of Pavement Research and Technology 2014;7(6):434–444.

FAA. Standards for Specifying Construction of Airports. FAA Advisory Circular (AC) No: 150/5370-10G, 2014.

FAA. Use of Nondestructive Testing in the Evaluation of Airport Pavements. FAA Advisory Circular (AC) No: 150/5370-11B, 2011.

FAA. Airport Pavement Design and Evaluation. FAA Advisory Circular (AC) No: 150/5320-6F, 2016.

Fathi, A., Mazari, M., Saghafi, M., Hosseini, A., & Kumar, S. Parametric Study of Pavement Deterioration Using Machine Learning Algorithms. In Airfield and Highway Pavements 2019: Innovation and Sustainability in Highway and Airfield Pavement Technology (pp. 31-41). Reston, VA: American Society of Civil Engineers.

Gopalakrishnan K, Thompson MR, Manik A. Rapid finite-element based airport pavement moduli solutions using neural networks. International Journal of Computational Intelligence 2006;3(1):63–71.

Nazarnia, H., & Sarmasti, H. Characterizing infrastructure resilience in disasters using dynamic network analysis of consumers’ service disruption patterns. Civil Engineering Journal, 2018, 4(10), 2356-2372.

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