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Developing Rigid Airport Pavement Multiple-Slab Response Models for Top-Down Cracking Mode using Artificial Neural Networks

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ABSTRACT

The Federal Aviation Administration (FAA) has recognized for some time that its current rigid pavement design model, involving a single slab loaded at one edge by a single aircraft gear, is inadequate to account for top-down cracking. Thus, one of the major observed failure modes for rigid pavements is poorly represented in the FAA Rigid and Flexible Iterative Elastic Layer Design (FAARFIELD) program. A research version of the FAARFIELD design software has been developed (FAARFIELD 2.0), in which the single-slab three-dimensional finite element (3D-FE) response model is replaced by a 4-slab 3D-FE model with initial temperature curling to produce reasonable thickness designs accounting for top-down cracking behavior. However, the long and unpredictable run times associated with the 4-slab model and curled slabs make routine design with this model impractical. In this paper, use of artificial intelligence (AI)-based alternatives such as artificial neural networks (ANNs) with potential for producing accurate stress predictions in a fraction of the time needed to perform a full 3D-FE computation has been investigated. In the development of ANN models, a synthetic database of FAARFIELD input-output pairs representing a number of realistic scenarios were developed. Moreover, ANN models for only mechanical and simultaneous mechanical and thermal loading cases were developed and accuracy predictions of these models were documented. It was observed that very high accuracies were achieved in predicting pavement responses for all cases investigated.

INTRODUCTION

Airport pavements are designed to withstand repeated loading imposed by aircraft, to resist abrasive action of traffic, and to endure deterioration induced by adverse weather conditions (e.g., extreme hot or cold weather) and other influences. A typical civil airport is serviced by a fleet of aircraft with different weights and gear configurations and the airport pavement is thus designed to withstand the repeated traffic loading of the entire range of aircraft, not just the heaviest aircraft (*1*), over many years. Historical airport pavement design methodologies have largely been based on empirical research and field performance. With the arrival of New Large Aircraft (NLA) and the associated design challenges for pavements, including increasing airplane weights and complex gear configurations, the FAA adopted layered elastic theory for flexible airport pavement design and three-dimensional finite element (3D-FE) procedures for rigid airport pavement design. These mechanistic-based design methodologies, implemented in the FAA Rigid and Flexible Iterative Elastic Layer Design (FAARFIELD) program, are considered robust and can be adapted for addressing future gear configurations without modifying the underlying procedures (*1*).

For rigid pavement design, FAARFIELD uses the 3D-FE model, NIKE3D_FAA (implemented as a dynamic link library written in FORTRAN), to compute the maximum horizontal stress at the bottom edge of the Portland Cement Concrete (PCC) slab as the pavement structural life predictor. The NIKE3D_FAA (sometimes referred to as just NIKE3D) is a modification of the NIKE3D program originally developed by the Lawrence Livermore National Laboratory (LLNL) of the U.S. Department of Energy (*2*, *3*). By limiting horizontal stress at the bottom of the PCC slab, cracking of the surface layer, the only rigid pavement failure mode considered by FAARFIELD, is controlled. It does not consider the failure of subbase and subgrade layers. For a given airplane traffic mix over a particular subgrade/subbase, FAARFIELD provides the required rigid pavement slab thickness (*4*).

The FAA has also developed FEAFAA (Finite Element Analysis – FAA), which makes use of NIKE3D, as a stand-alone tool for 3D FE analysis of multiple-slab rigid airport pavements and overlays. It computes accurate responses (deflections, stresses, and strains) of rigid pavements to individual aircraft landing gear loads. Note that FEAFAA is intended to be more a research and analysis tool than a design tool.

FAA prioritized to extend design life of pavements to 40 years as a new pavement design policy. To reach that goal, current rigid pavement design methodology must be improved in different ways. FAA's current rigid pavement design model, involving a single slab loaded at one edge by a single aircraft gear, is inadequate to account for top-down cracking. Thus, one of the major observed failure modes for rigid pavements is poorly accounted for in the FAARFIELD rigid design procedure. A research version of the FAARFIELD design software in which the single-slab three-dimensional finite element (3D-FE) response model is replaced by a 4-slab 3D-FE model with initial temperature curling to produce reasonable thickness designs accounting for top-down cracking behavior has been developed (FAARFIELD 2.0). However, the long and unpredictable run times associated with the 4-slab model and curled slabs make routine design with this model impractical. To expand the FAARFIELD design model beyond the current reduced one-slab model, the FAA is seeking practical alternatives to running the 3D-FEM stress computation as client software. Artificial intelligence (AI) based alternatives such as artificial neural networks (ANNs), with potential to produce accurate stress predictions in a fraction of the time needed to perform a full 3D-FE computation, can be among those practical alternatives.

The capability of ANN-based surrogate response models to successfully compute lateral and longitudinal tensile stresses as well as deflections at the bottom of jointed concrete airfield pavements as a function of type, level, and location of the applied gear load, slab thickness, slab modulus, subgrade support, pavement temperature gradient, and the load transfer efficiencies of the joints has already been illustrated by many studies (*5*, *6*, *7*).

The objective of this paper is to develop ANN-based surrogate computational response models or procedures (suitable for implementation in FAARFIELD 2.0) that return a close estimate of the top-down bending stress computed by NIKE3D in rigid airport pavements. This will enable faster 3D-FE computations of design stresses in FAARFIELD 2.0 making it suitable for routine design. Note that, to develop these ANN models, FEAFAA, the research-grade version of FAARFIELD, was employed. Namely, a synthetic database consisting of FEAFAA input parameters and the associated critical pavement responses needed to be created to develop ANN-based surrogate computational response models. This database was developed using the following process automation:

- Generate several cases with randomly generated FEAFAA input parameters within specified ranges (step 1)
- Run FEAFAA one case at a time (step 2)
- Extract critical pavement responses from FEAFAA output file (step 3)
- Enter the extracted critical pavement responses into the database (step 4)
- Repeat steps 2-4 for all the generated cases in step 1

In the FEAFAA batch runs, two different loading cases were considered and ANN models were developed for these two cases: mechanical load only, and simultaneous mechanical and temperature loading. ANN models were developed by using all individual input parameters as independent inputs and critical pavement responses produced by FEAFAA as outputs.

SYNTHETIC DATABASE DEVELOPMENT

To develop an extensive database of input-output records from FEAFAA 2.0, the C# programming tool together with the AutoIt® scripting tool was utilized to minimize the required time to feed the software with inputs and to post-process, minimizing human involvement in the process. The developed tool can automatically perform batch runs, obtain the outputs, and perform the post processing. The post-processing includes extracting the critical pavement responses from the output, and also must be able to separately pinpoint the exact locations of critical pavement responses for top and bottom of the slab. Also, for each FEAFAA run, the types of critical normal stresses were categorized and specified as critical tensile and compressive stresses. The pavement responses on top of the slabs were considered to be critical because they play a major role in top-down cracking. To ensure that the ANN models can successfully predict the pavement responses associated with top-down cracking mode, a group of 439 FEAFAA runs (after eliminating some erroneous cases from a total of 500 cases) using only mechanical loading was carried out. A batch run of 500 cases with simultaneous mechanical and thermal loading was also performed. In these cases, a pavement layer configuration composed of an infinite subgrade, a granular base, and a PCC layer was employed. Pavement parameters to characterize material, loading, pavement size, and joint stiffness parameters were varied by assigning random numbers within a predefined range, determined from the FEAFAA hardcoded values and engineering judgment. A normal distribution within the predefined range for each variable was ensured. A preliminary analysis was carried out to determine minimum number of samples to be used for each variable in the batch run. Using a group of 100, 200, 300, and 500 normally distributed random numbers within the predefined range, batch runs were conducted and predicted critical pavement responses were compared with those produced by FEAFAA. The accuracies of models using 100, 200, 300 and 500 samples were also compared to find out what should be the minimum sample size for producing accurate ANN models. It was found out that 500 samples produce ANN models with sufficient accuracy. To quantify the accuracy, R^2 (Coefficient of determination) and MSE (Mean squared error) values were presented throughout this paper.

Table 1 displays the FEAFAA input parameters and their ranges used for the batch runs. Note that the highlighted input parameters indicate that these parameters were not varied.

TABLE 1 Ranges of Inputs Used for FEAFAA Batch Runs

Inputs		**Range**	
		Min	**Max**
PCC Slab	Modulus (psi)	3E+6	7E+6
	Thickness (in.)	10	24
	Poisson Ratio	0.15	0.20
Granular Subbase	Modulus (psi)	15,000	50,000
	Thickness (in.)	20	50
	Poisson Ratio	0.35	
Subgrade	Modulus (psi)	3,000	30,000
	Poisson Ratio	0.4	
Slab Dimension (ft.)		20	30
Slab Number of Elements		30	
Number of Slabs		9	
Foundation Number of Elements		30	
Loading Angle		0	90
Temperature Gradient		2.3	
Thermal Coefficient(1/^{o}F)		4.1E-6	7.2E-6
Dowel Diameter (in.)		0.5	1.5
Dowel Spacing (ft.)		6	24
Joint Opening (in.)		0.125	0.625

A Boeing B777-300ER, with a gross weight of 777,000 lbs., was used as the representative aircraft for all cases. Because of symmetry of the problem, only one of the two main aircraft gears was analyzed. Nine slabs with varying slab dimensions (L_x, and L_y), loading angles (θ_g), and gear locations (x_g and y_g) were used in the analysis (Figure 1).

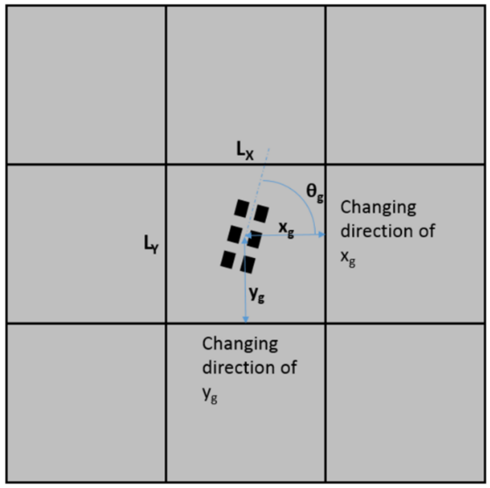


FIGURE 1 Aircraft loading conditions.

ANN MODEL DEVELOPMENT

ANN models were developed for both mechanical-load-only and simultaneous mechanical and thermal load cases. In the ANN model development, a two-layer feed-forward network was trained using a Levenberg-Marquardt algorithm (LMA) in the MATLAB environment.

Mechanical-Load-Only Case

Using all different input parameters with their ranges, a batch run of 439 cases simulating simultaneous mechanical loading only were performed and critical pavement responses required for development of ANN models were obtained.

As shown in Figure 2, 14 input parameters are to be used in the ANN model development. Among these 14 input parameters, three represent the slab properties, three represent pavement foundation properties, three represent loading location, two represent pavement size, and the other three represent the joint stiffness properties of the pavement system.

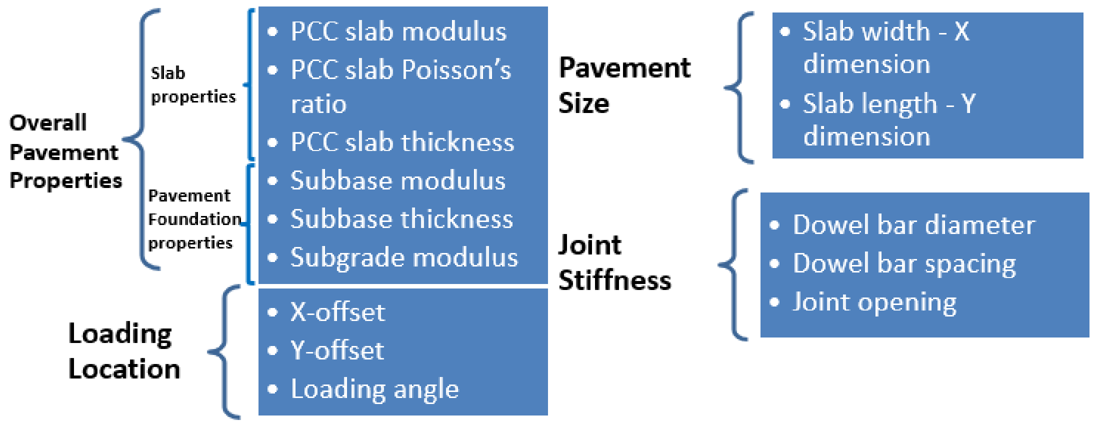


FIGURE 2 Fourteen individual input parameters used in the development of ANN models (Mechanical load only case).

For top-down cracking mode, stresses and deflections at the top of the slab surface are of great interest, so critical pavement stresses and deflections at the top of the slab surface were extracted for each case and used as outputs in the ANN model development. The critical pavement responses used as individual outputs in the ANN model development are as follows:

- $\sigma_{xx,\ max,\ top\text{-}tensile}$
- $\sigma_{yy,\ max,\ top\text{-}tensile}$
- $\tau_{xy,\ max,\ top}$
- $\delta_{\ max}$

Where,

$\sigma_{xx,\ max,\ top\text{-}tensile}$ = Maximum tensile stress in x direction on top of the slab surface
$\sigma_{yy,\ max,\ top\text{-}tensile}$ = Maximum tensile stress in y direction on top of the slab surface
$\tau_{xy,\ max,\ top}$ = Maximum shear stress on top of the slab surface
$\delta_{\ max}$ = Maximum deflection

Figure 3 shows the ANN network architecture employed in the model development. As can be seen in the figure, the ANN network consists of 14 inputs, one hidden layer with 40 hidden neurons, and one output layer. The choice of forty hidden layers was made in the ANN network architecture based on the results of a sensitivity analysis conducted for this study. The sensitivity analysis was carried out using 10, 20, and 40 hidden layers for all cases. In some cases, use of 10 and 20 hidden layers could not produce models as accurate as when 40 hidden layers are used so, for the sake of consistency, 40 hidden layers were used for all cases in this study.

Note that a separate ANN model was developed to predict each pavement response, so one output layer showing the related pavement response to be predicted and the ANN model to be developed is shown in the network architecture (Figure 3).

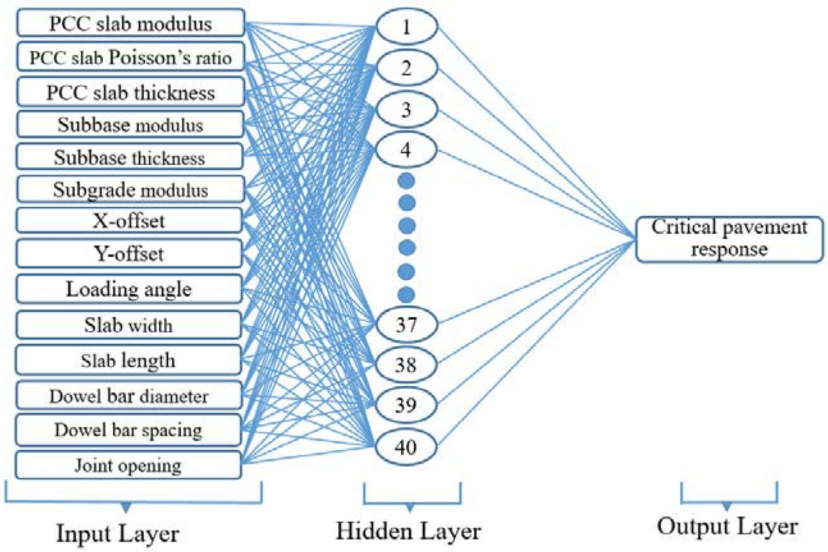
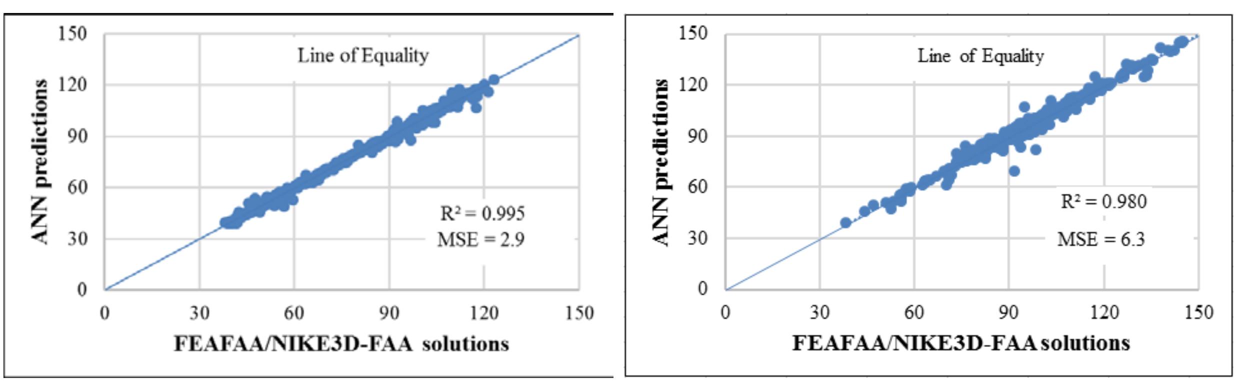
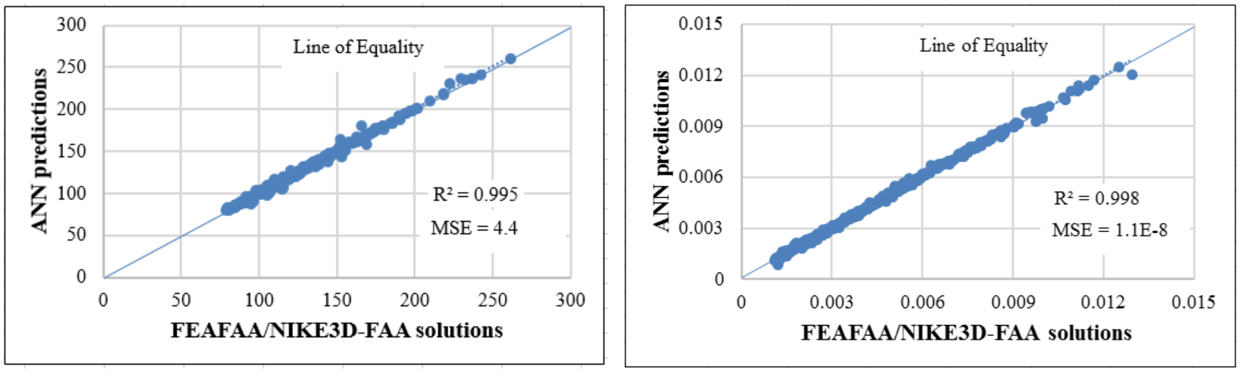


FIGURE 3 ANN network architecture (individual input parameters, mechanical load only case).

Figure 4 shows pavement response comparisons between the FEAFAA/NIKE3D-FAA solutions and ANN model solutions for (a) $\sigma_{xx,\ max,\ top\text{-}tensile}$, (b) $\sigma_{yy,\ max,\ top\text{-}tensile}$, (c) $\tau_{xy,\ max,\ top}$, and (d) δ_{max}. For all pavement response types, in the ANN model development, 307, 66, and 66 cases were used for training, testing, and validation, respectively. For all pavement response types, ANN models successfully replicated FEAFAA/NIKE3D-FAA pavement response solutions. It is also important to note that validation and test sets produced accuracies similarly high as the training set in all pavement response types. This is a proof of ANN models' lack of generalization (i.e., they did not memorize the relationship) and so they are robust and valid.



(a) (b)



(c) (d)

FIGURE 4 FEAFAA/NIKE3D-FAA solutions vs. ANN solutions for (a) $\sigma_{xx,\ max,\ top\text{-}tensile}$ (psi), (b) $\sigma_{yy,\ max,\ top\text{-}tensile}$ (psi), (c) $\tau_{xy,\ max,\ top}$ (psi), and (d) δ_{max} (inches) (individual input parameters, mechanical load only case).

Simultaneous Mechanical and Thermal Loading Case

Using all the different input parameter combinations with their ranges, a batch run of 500 cases simulating simultaneous mechanical and thermal loading were performed and critical pavement responses required for development of ANN models were obtained.

In this approach, all individual varied input parameters were used in ANN models as input parameters. Figure 5 shows a total of 16 input parameters that must be used in the ANN model development for that case. As can be seen in Figure 5, the only difference between the simultaneous mechanical and thermal loading case and the mechanical loading only case is the inclusion of two parameters to simulate thermal loading; these are shown in the figure as slab temperature properties.

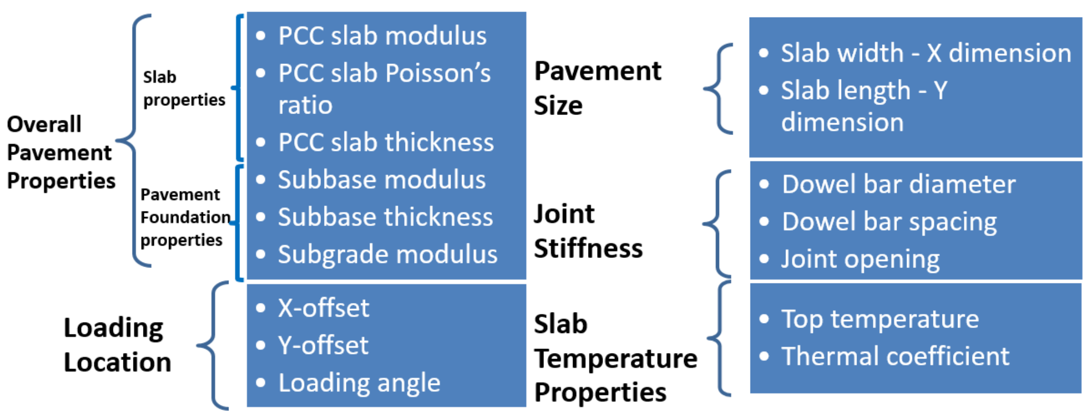


FIGURE 5 Sixteen types of individual input parameters (simultaneous mechanical and thermal loading case).

In this case, as the ANN network architecture, 16 inputs, one hidden layer with 40 hidden neurons along with one output layer was used.

Figure 6 shows pavement response comparisons between the FEAFAA/NIKE3D-FAA solutions and ANN solutions for (a) $\sigma_{xx,\ max,\ top\text{-}tensile}$, (b) $\sigma_{yy,\ max,\ top\text{-}tensile}$, (c) $\tau_{xy,\ max,\ top}$ and (d)

δ_{max}. For all response types, 350, 75 and 75 cases were used for training, testing and validation, respectively. Similar to the previous findings, for all pavement response types, ANN models successfully reproduced FEAFAA/NIKE3D-FAA solutions.

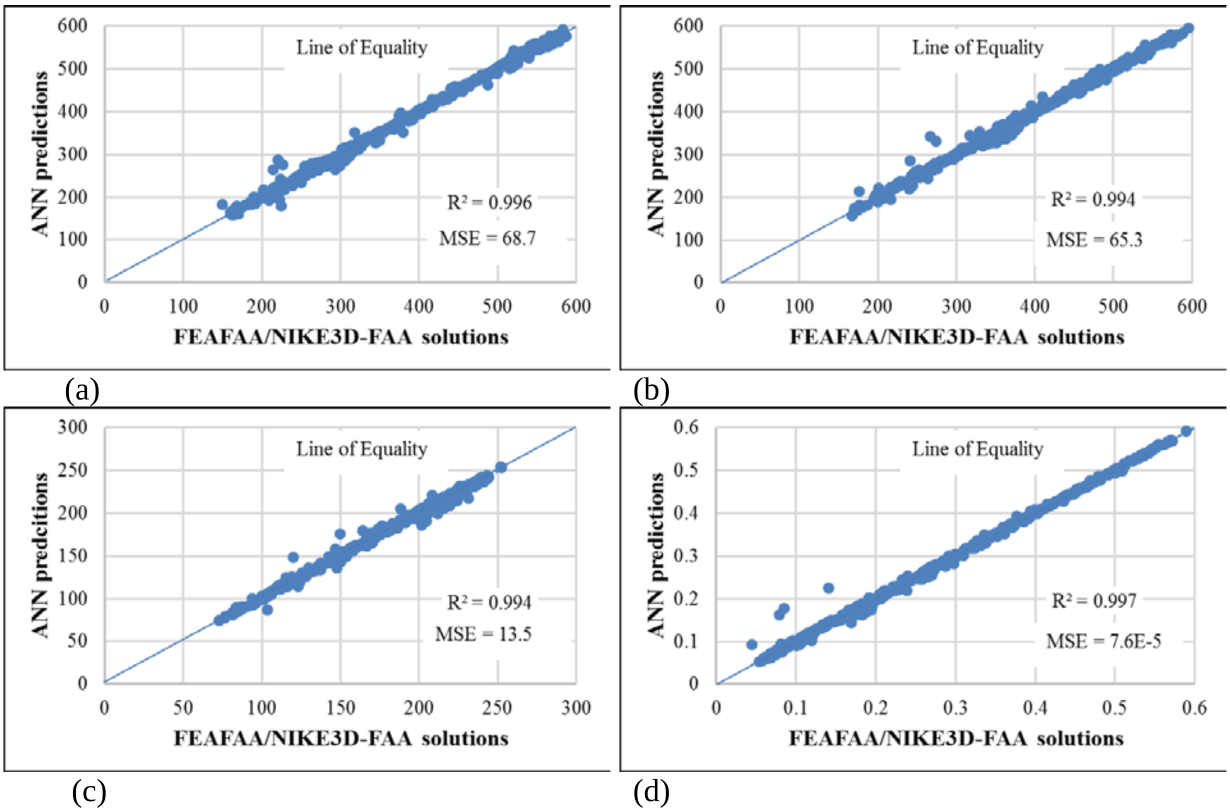


FIGURE 6 FEAFAA/NIKE3D-FAA solutions vs. ANN solutions for (a) $\sigma_{xx, max, top\text{-}tensile}$ (psi), (b) $\sigma_{yy, max, top\text{-}tensile}$ (psi), (c) $\tau_{xy, max, top}$ (psi), and (d) δ_{max} (inches) (individual input parameters, simultaneous mechanical and thermal load case).

Table 2 shows the accuracy comparisons of the ANN models with respect to predicting pavement responses with the accuracies expressed in terms of R^2 and Mean Squared Error (MSE). As can be seen in the table, ANN models successfully predicted pavement responses for both mechanical load and simultaneous mechanical and thermal load cases.

TABLE 2 Accuracy Comparison of the ANN Models in Predicting Pavement Responses for Different Cases

LOADING CASE	ACCURACY (R^2/MSE)			
	$\sigma_{xx, max, top\text{-}tensile}$	$\sigma_{yy, max, top\text{-}tensile}$	$\tau_{xy, max, top}$	δ_{max}
Mechanical load only case	0.995 / 2.9	0.980 / 6.3	0.995 / 4.4	0.998 / 1.1-E8

Simultaneous mechanical and temperature load case	0.996 / 68.7	0.994 / 65.3	0.994 / 13.5	0.997 / 7.6E-5

SUMMARY, CONCLUSIONS AND FUTURE WORK

FAA is seeking practical alternatives to running the 3D-FEM stress computation that can reduce the time required to give accurate stress predictions. Artificial intelligence (AI) based alternatives such as artificial neural networks (ANNs) have great potential and have been successfully used in pavement engineering to solve similar problems for decades.

This paper investigated the feasibility of developing ANN-based surrogate computational response models or procedures (suitable for implementation in FAARFIELD 2.0) that return close estimates of the top-down bending stress computed by NIKE3D in rigid airport pavements. These models would enable faster 3D-FE computations of design stresses in FAARFIELD 2.0, making it suitable for routine design. Note that, to develop these ANN models, FEAFAA, the research-grade version of FAARFIELD was utilized.

To develop ANN-based surrogate computational response models, a synthetic database consisting of FEAFAA input parameters and the associated critical pavement responses was created. In the FEAFAA batch runs, two different loading cases were considered and ANN models for these two cases were developed: mechanical load only, and simultaneous mechanical and temperature loading.

Specific conclusions of this paper are listed below:

- ANN was found to be a promising alternative in producing very close estimates of the top-down bending stress computed by NIKE3D in rigid airport pavements. By using ANN models, very accurate stress predictions can be produced in a fraction of time compared to the significant amount of time needed to perform a 3D-FE computation. For example, stress predictions for thousands of cases can be predicted in seconds using ANN models, compared to days, if not months, using 3D-FE computation.
- Future studies will focus on creating ANN models for other airplane types available in FEAFAA's airplane library. The current airplane library includes 26 types of generic, 32 types of Airbus, 38 types of Boeing, 18 types of other commercial, 53 types of general aviation, 10 types of military, and 8 types of external library.

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