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

Abstract

The Federal Aviation Administration (FAA) has recognized for some time that its current rigid 44 pavement design model, involving a single slab loaded at one edge by a single aircraft gear, is 45 inadequate to account for top-down cracking. Thus, one of the major observed failure modes for 46 rigid pavements is poorly represented in the FAA Rigid and Flexible Iterative Elastic Layer 47 Design (FAARFIELD) program. A research version of the FAARFIELD design software has 48 been developed (FAARFIELD 2.0), in which the single-slab three-dimensional finite element 49 (3D-FE) response model is replaced by a 4-slab 3D-FE model with initial temperature curling to 50 produce reasonable thickness designs accounting for top-down cracking behavior. However, the 51 long and unpredictable run times associated with the 4-slab model and curled slabs make routine 52 design with this model impractical. In this paper, use of artificial intelligence (AI)-based 53 alternatives such as artificial neural networks (ANNs) with potential for producing accurate 54 stress predictions in a fraction of the time needed to perform a full 3D-FE computation has been 55 investigated. In the development of ANN models, a synthetic database of FAARFIELD input- 56 output pairs representing a number of realistic scenarios were developed. Moreover, ANN 57 models for only mechanical and simultaneous mechanical and thermal loading cases were 58 developed and accuracy predictions of these models were documented. It was observed that very 59 high accuracies were achieved in predicting pavement responses for all cases investigated.

Keywords

Airport runways, Neural networks, Pavement design, Rigid pavements

Disciplines

Civil Engineering | Structural Engineering

Comments

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3 **for Top-Down Cracking Mode using Artificial Neural Networks**

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42 ABSTRACT

43 The Federal Aviation Administration (FAA) has recognized for some time that its current rigid
44 pavement design model, involving a single slab loaded at one edge by a single aircraft gear, is
45 inadequate to account for top-down cracking. Thus, one of the major observed failure modes for
46 rigid pavements is poorly represented in the FAA Rigid and Flexible Iterative Elastic Layer
47 Design (FAARFIELD) program. A research version of the FAARFIELD design software has
48 been developed (FAARFIELD 2.0), in which the single-slab three-dimensional finite element
49 (3D-FE) response model is replaced by a 4-slab 3D-FE model with initial temperature curling to
50 produce reasonable thickness designs accounting for top-down cracking behavior. However, the
51 long and unpredictable run times associated with the 4-slab model and curled slabs make routine
52 design with this model impractical. In this paper, use of artificial intelligence (AI)-based
53 alternatives such as artificial neural networks (ANNs) with potential for producing accurate
54 stress predictions in a fraction of the time needed to perform a full 3D-FE computation has been
55 investigated. In the development of ANN models, a synthetic database of FAARFIELD input-
56 output pairs representing a number of realistic scenarios were developed. Moreover, ANN
57 models for only mechanical and simultaneous mechanical and thermal loading cases were
58 developed and accuracy predictions of these models were documented. It was observed that very
59 high accuracies were achieved in predicting pavement responses for all cases investigated.

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74 INTRODUCTION

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

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

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

104 FAA prioritized to extend design life of pavements to 40 years as a new pavement design
105 policy. To reach that goal, current rigid pavement design methodology must be improved in
106 different ways. FAA's current rigid pavement design model, involving a single slab loaded at
107 one edge by a single aircraft gear, is inadequate to account for top-down cracking. Thus, one of
108 the major observed failure modes for rigid pavements is poorly accounted for in the
109 FAARFIELD rigid design procedure. A research version of the FAARFIELD design software in
110 which the single-slab three-dimensional finite element (3D-FE) response model is replaced by a
111 4-slab 3D-FE model with initial temperature curling to produce reasonable thickness designs
112 accounting for top-down cracking behavior has been developed (FAARFIELD 2.0). However,
113 the long and unpredictable run times associated with the 4-slab model and curled slabs make
114 routine design with this model impractical. To expand the FAARFIELD design model beyond
115 the current reduced one-slab model, the FAA is seeking practical alternatives to running the 3D-
116 FEM stress computation as client software. Artificial intelligence (AI) based alternatives such as
117 artificial neural networks (ANNs), with potential to produce accurate stress predictions in a

118 fraction of the time needed to perform a full 3D-FE computation, can be among those practical
119 alternatives.

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

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

134

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

141

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

146

147 **SYNTHETIC DATABASE DEVELOPMENT**

148 To develop an extensive database of input-output records from FEAFAA 2.0, the C#
149 programming tool together with the AutoIt® scripting tool was utilized to minimize the required
150 time to feed the software with inputs and to post-process, minimizing human involvement in the
151 process. The developed tool can automatically perform batch runs, obtain the outputs, and
152 perform the post processing. The post-processing includes extracting the critical pavement
153 responses from the output, and also must be able to separately pinpoint the exact locations of
154 critical pavement responses for top and bottom of the slab. Also, for each FEAFAA run, the
155 types of critical normal stresses were categorized and specified as critical tensile and
156 compressive stresses. The pavement responses on top of the slabs were considered to be critical
157 because they play a major role in top-down cracking. To ensure that the ANN models can
158 successfully predict the pavement responses associated with top-down cracking mode, a group of
159 439 FEAFAA runs (after eliminating some erroneous cases from a total of 500 cases) using only
160 mechanical loading was carried out. A batch run of 500 cases with simultaneous mechanical and
161 thermal loading was also performed. In these cases, a pavement layer configuration composed of
162 an infinite subgrade, a granular base, and a PCC layer was employed. Pavement parameters to

163 characterize material, loading, pavement size, and joint stiffness parameters were varied by
 164 assigning random numbers within a predefined range, determined from the FEAFAA hardcoded
 165 values and engineering judgment. A normal distribution within the predefined range for each
 166 variable was ensured. A preliminary analysis was carried out to determine minimum number of
 167 samples to be used for each variable in the batch run. Using a group of 100, 200, 300, and 500
 168 normally distributed random numbers within the predefined range, batch runs were conducted
 169 and predicted critical pavement responses were compared with those produced by FEAFAA. The
 170 accuracies of models using 100, 200, 300 and 500 samples were also compared to find out what
 171 should be the minimum sample size for producing accurate ANN models. It was found out that
 172 500 samples produce ANN models with sufficient accuracy. To quantify the accuracy, R^2
 173 (Coefficient of determination) and MSE (Mean squared error) values were presented throughout
 174 this paper.

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

177

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/°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

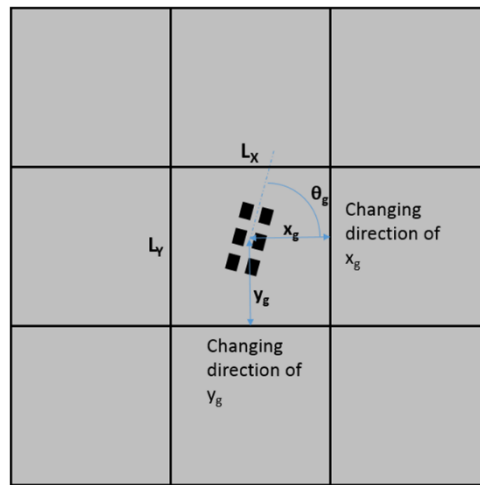
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A Boeing B777-300ER, with a gross weight of 777,000 lbs., was used as the representative aircraft for all cases. Because of symmetry of the problem, only one of the two

181 main aircraft gears was analyzed. Nine slabs with varying slab dimensions (L_x , and L_y), loading
 182 angles (θ_g), and gear locations (x_g and y_g) were used in the analysis (Figure 1).
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FIGURE 1 Aircraft loading conditions.

186 ANN MODEL DEVELOPMENT

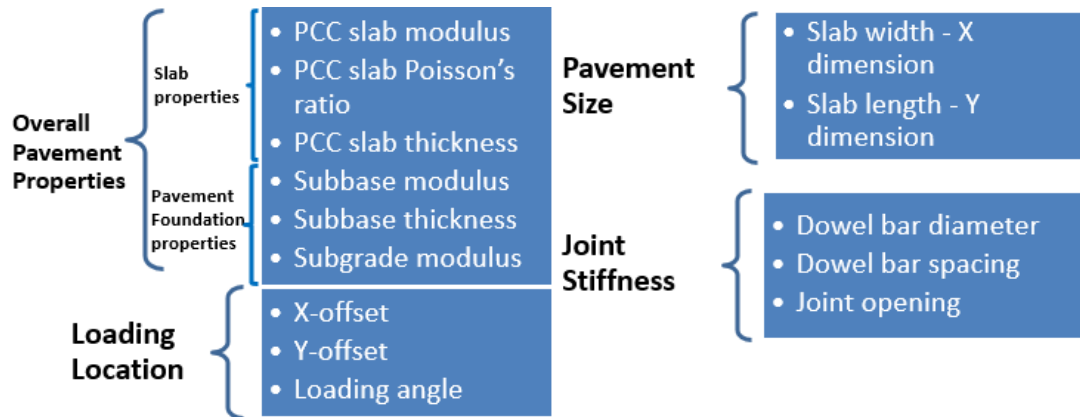
187 ANN models were developed for both mechanical-load-only and simultaneous mechanical and
 188 thermal load cases. In the ANN model development, a two-layer feed-forward network was
 189 trained using a Levenberg-Marquardt algorithm (LMA) in the MATLAB environment.

190 Mechanical-Load-Only Case

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

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

198



199

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

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

- 206 • $\sigma_{xx, \max, \text{top-tensile}}$
- 207 • $\sigma_{yy, \max, \text{top-tensile}}$
- 208 • $\tau_{xy, \max, \text{top}}$
- 209 • δ_{\max}

210 Where,

211 $\sigma_{xx, \max, \text{top-tensile}}$ = Maximum tensile stress in x direction on top of the slab surface

212 $\sigma_{yy, \max, \text{top-tensile}}$ = Maximum tensile stress in y direction on top of the slab surface

213 $\tau_{xy, \max, \text{top}}$ = Maximum shear stress on top of the slab surface

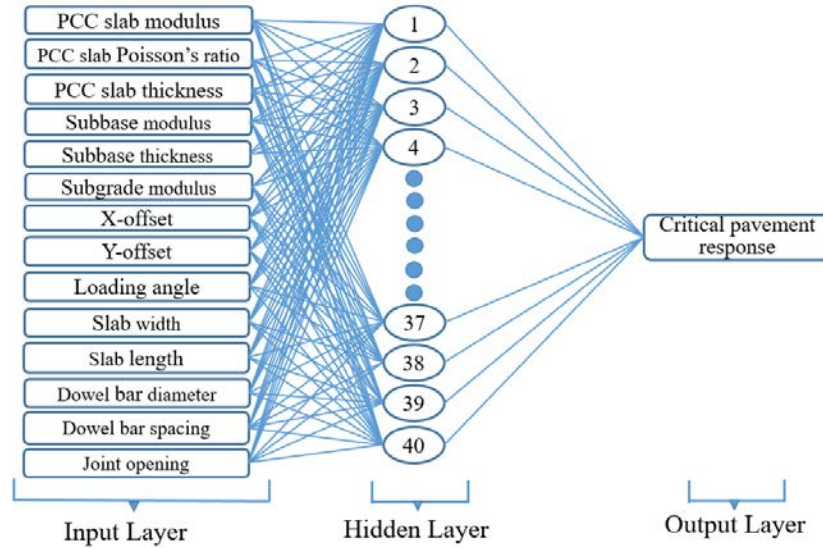
214 δ_{\max} = Maximum deflection

215

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

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

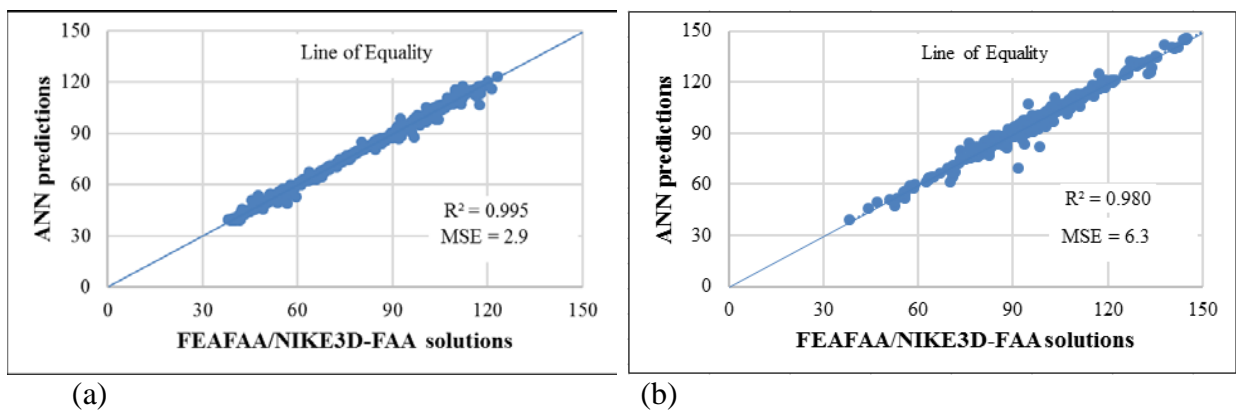
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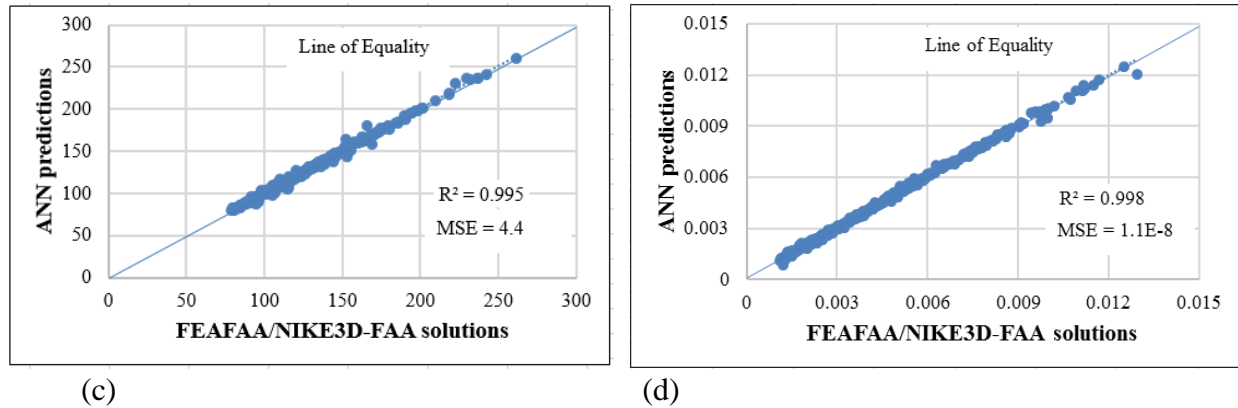
229 **FIGURE 3 ANN network architecture (individual input parameters, mechanical load only**
 230 **case).**

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



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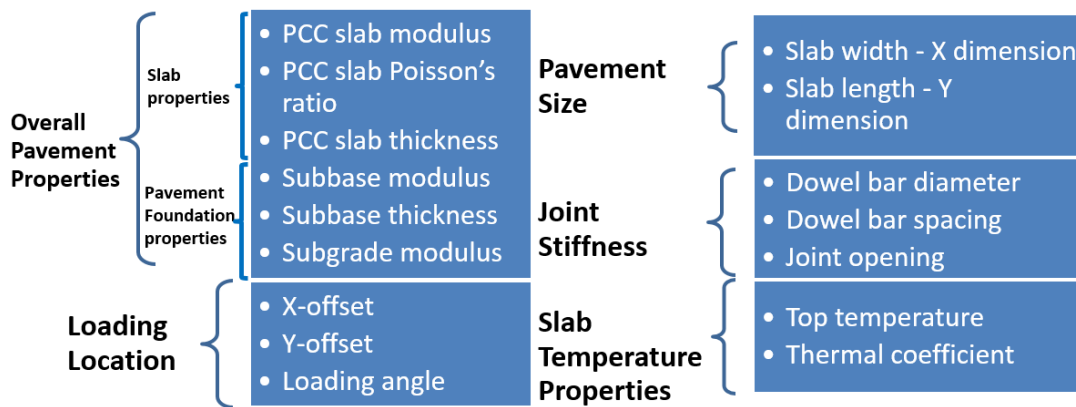
243 **FIGURE 4 FEAFAA/NIKE3D-FAA solutions vs. ANN solutions for (a) $\sigma_{xx, \max, \text{top-tensile}}$ (psi),**
 244 **(b) $\sigma_{yy, \max, \text{top-tensile}}$ (psi), (c) $\tau_{xy, \max, \text{top}}$ (psi), and (d) δ_{\max} (inches) (individual input**
 245 **parameters, mechanical load only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

246 **Simultaneous Mechanical and Thermal Loading Case**

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

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

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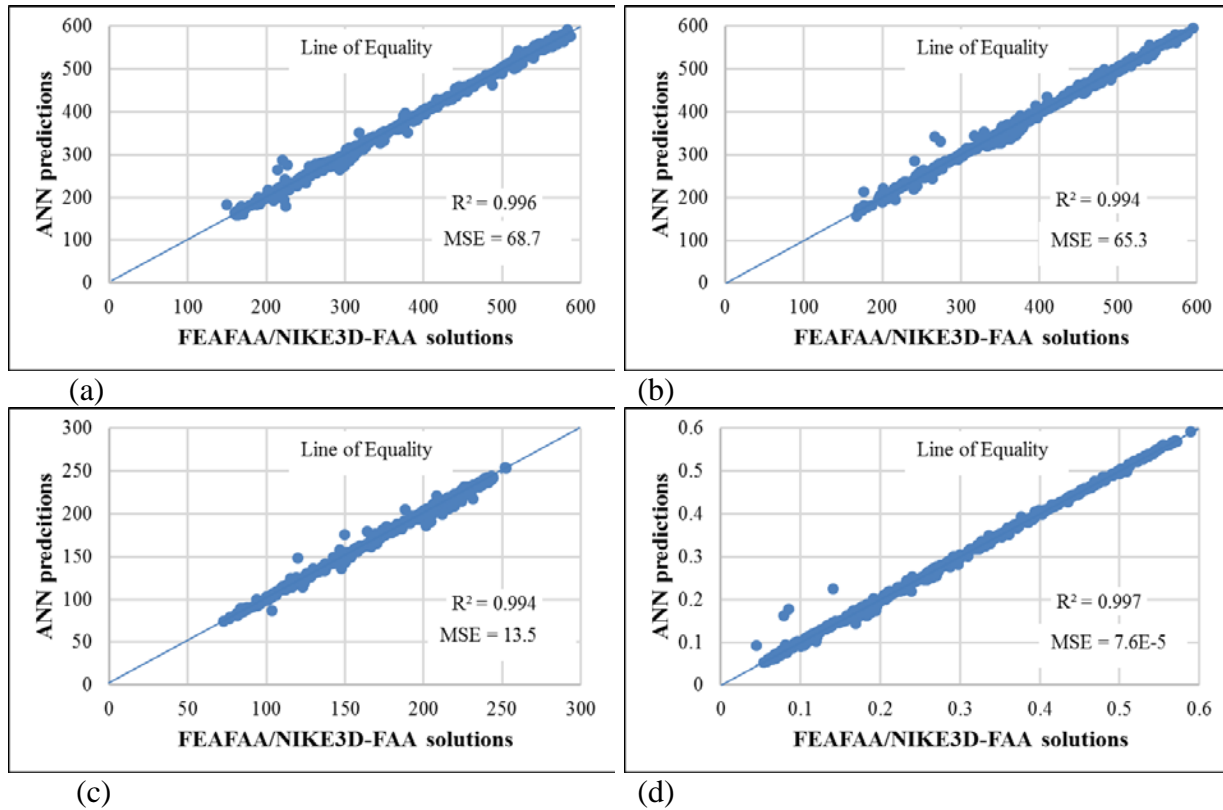
258 **FIGURE 5 Sixteen types of individual input parameters (simultaneous mechanical and**
 259 **thermal loading case).**

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

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

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

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 270

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

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

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

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

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282
283

Simultaneous mechanical and temperature load case	0.996 / 68.7	0.994 / 65.3	0.994 / 13.5	0.997 / 7.6E-5
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284

SUMMARY, CONCLUSIONS AND FUTURE WORK

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

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

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

300 Specific conclusions of this paper are listed below:

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

311

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317 a standard, specification, or regulation.

318

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