Iowa State University

From the Selected Works of Halil Ceylan

2007

Artificial Neural Networks for Analyzing Concrete Airfield Pavements Serving the Boeing B-777 Aircraft

Halil Ceylan
Erol Tutumluer
Ernest J. Barenberg

Available at: https://works.bepress.com/halil_ceylan/13/

Artificial Neural Networks for Analyzing Concrete Airfield Pavements Serving the Boeing B-777 Aircraft

HALIL CEYLAN, EROL TUTUMLUER, AND ERNEST J. BARENBERG

An artificial neural network (ANN) model has been trained with the results of the ILLI-SLAB finite element program and has been used to predict stresses and deflections in jointed concrete airfield pavements serving the Boeing B-777 aircraft. The trained ANN model produces stresses and deflections with average errors of less than 0.5 percent of those obtained directly from the finite element analyses. Use of the ANN model has been found to be very effective for correctly predicting ILLI-SLAB stresses and deflections, in less than 1 s, with no requirements of complicated finite element inputs. On the other hand, elastic layered programs (ELPs) currently are being used in mechanistic-based pavement design procedures for the analysis of jointed concrete pavements. Corrections are required to such ELP solutions to account for the effects of finite slab size, load location on the slab, and load transfer efficiencies of the joints. This can be accomplished by using the ANN model, which is being expanded to handle all possible aircraft gear configurations with multiple-wheel loading conditions by the use of the superposition principle. As demonstrated for the solution of the B-777 aircraft gear loadings, trained neural network models eventually will enable pavement engineers to easily incorporate current sophisticated state-of-the-art technology into routine practical design.

Many theoretical models used in the mechanistic design of pavement systems assume the layers to extend infinitely far in the horizontal directions. Design procedures such as the Asphalt Institute method (1), the shell method (2), and Layered Elastic Design-FAA (LED-FAA) (3) all employ elastic layered programs (ELPs) for the analysis of pavement sections. Although these programs may perform reasonably well for analyzing pavements without discontinuities (i.e., flexible pavements), they are not the best means with which to facilitate rigid pavement design. The problem that occurs when trying to apply linear elastic layered theory to rigid pavements is that of a finite slab size with varying levels of load transfer across the joints. The joints within a portland cement concrete (PCC) pavement naturally conflict with the assumption of an infinite, semielastic half-space concept utilized in ELPs. The location of wheel loading relative to edges and joints becomes important in rigid pavements because in most cases, a complete load transfer in the joints separating two slabs cannot be achieved. As a result, the maximum bending stresses and deflections in rigid pavements predicted from a linear elastic layered analysis do not at all correspond to the actual stresses and deflections these pavements will experience in the field.

For the analysis of jointed concrete pavements serving the Boeing B-777 aircraft, the use of a more sophisticated analysis tool, such as the finite element model, is a necessity for a better design. ILLI-SLAB (4-6) is a validated finite element program that is available for analyzing rigid pavements. In this study, ILLI-SLAB was used

as the primary analysis tool for the solution of airfield concrete slab stresses and deflections under the six-wheel tri-tandem-type B-777 gear loading conditions.

Artificial neural networks (ANNs) are valuable computational tools that are used increasingly to solve resource-intensive complex problems as an alternative to using more traditional techniques, such as the finite element method. In a recent successful application, the use of ANNs was introduced for the analysis of jointed concrete pavement responses under a dual-wheel-type aircraft gear loading (7). An ANN model was trained with the results of the ILLI-SLAB solutions, which was intended to enable pavement engineers to easily incorporate current sophisticated finite element methodology into routine practical design.

This paper primarily focuses on the development and performance of a comprehensive ANN model for the analyses of B-777 aircraft gear loading. In addition to various load locations (slab interior, corners, edges) and joint load transfer efficiencies, a wide range of realistic airfield slab thicknesses and subgrade supports have been considered as ANN input conditions. More than 38,000 ILLI-SLAB analyses have provided the design parameters and the pavement responses as inputs for training the ANN model. Consideration was given only to the loading of a jointed slab assembly under the tri-tandem-type Boeing B-777 aircraft gear configuration. The trained ANN model gave maximum bending stresses within an average error of 0.4 percent and maximum deflections within an average error of 0.5 percent of those obtained directly from ILLI-SLAB analyses.

RIGID PAVEMENT THEORY AND ILLI-SLAB FINITE ELEMENT METHOD PROGRAM

Jointed slab analysis was performed by using a finite element program referred to in the literature as ILLI-SLAB (4-6). This program was developed at the University of Illinois in the late 1970s for the structural analysis of jointed concrete slabs consisting of one or two layers, with either a smooth interface or complete bonding between layers. The ILLI-SLAB model is based on the classical theory for a medium-thick elastic plate resting on a Winkler foundation, and it can be used to evaluate the structural response of pavement systems with arbitrary crack or joint locations, of any slab size, and with any arbitrary loading combinations (8). Load transfer across joints and cracks can be provided by aggregate interlock or dowels or by combinations of the two. The model employs the 4-noded, 12-dof rectangular plate bending elements (ACM or RPB 12). Assumptions regarding the slab, base layer, overlay, subgrade, dowel bar, and aggregate interlock can be briefly summarized as follows:

1. Small deformation theory of an elastic, homogeneous medium-thick plate is employed for the slab, base, and overlay. Such a plate is assumed to be thick enough to carry transverse load by slab flexure instead of by in-plane forces, yet it is not so thick that transverse shear deformation becomes important. For this development the Kirchhoff theory is assumed, in which lines normal to the middle surface in the undeformed plate remain straight, unstretched, and normal to the middle surface of the deformed plate; each lamina parallel to the middle surface is in a state of plane stress; and no axial or in-plane shear stress develops due to loading.

2. The subgrade behaves as a Winkler foundation.

3. In the case of a bonded base or overlay, full strain compatibility exists at the interface; or for the unbonded case, shear stresses at the interface are nil.

4. Dowel bars at joints are linearly elastic and are located at the neutral axis of the slab.

5. When aggregate interlock is used for load transfer, load is transferred from one slab to an adjacent slab by shear. However, with dowel bars, some moment as well as shear may be transferred across the joints.

This model has been extensively tested by comparison of results with available theoretical solutions and results from experimental studies (6,9,10).

BACKPROPAGATION ANNs

A backpropagation-type ANN model was trained in this study with the results of the ILLI-SLAB finite element program and used as an analysis design tool for predicting stresses and deflections in jointed concrete airfield pavements. Backpropagation ANNs are very powerful and versatile networks that can be “taught” a mapping from one data space to another by using examples of the mapping to be learned. The term “backpropagation network” actually refers to a multilayered, feed-forward neural network trained by using an error backpropagation algorithm. The learning process performed by this algorithm is called “backpropagation learning” (11–15).

As with many ANNs, the connection weights in the backpropagation ANNs initially are selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct answers are then propagated backward through the network, and the connection weights are individually adjusted to reduce the error. After many examples have been propagated through the network many times, the mapping function is “learned” to within some error tolerance. This is called supervised learning because the network has to be shown the correct answers for it to learn. Backpropagation networks excel at data modeling with their superior function approximation capabilities (15,16).

ILLI-SLAB ANALYSIS OF CONCRETE SLABS

Concrete airfield pavements were represented by a four-slab assembly, each slab 7.62 m² (25 ft²). Figure 1 depicts the geometry and analysis conditions of the pavement sections, such as the constant slab size (L), standard tri-tandem loading applied on only one quadrant of the lower-left slab, and the standard finite element mesh used. The Young's modulus and the Poisson's ratio for the concrete slabs were set at 27 560 MPa (4,000 ksi) and 0.15, respectively. A total of 38,880

FIGURE 1 Geometry and analysis conditions for the four-slab concrete airfield pavement system.

ILLI-SLAB analysis runs were conducted with the four-slab assembly by varying a number of design parameters used to generate a neural network training database. Various loading locations (slab interior, corners, edges) and joint load transfer efficiencies (LTEs) chosen along x - and y -directions are tabulated in Table 1. LTEs were varied from 25 percent to 90 percent. Also given in Table 1 are the representative values of the slab thicknesses (t) and moduli of subgrade reaction (k) considered in the ILLI-SLAB finite element analyses, for a total of six input design parameters.

The standard tri-tandem gear loading on the pavement sections consisted of a 209.2-kN (47,025-lb) wheel load approximated as a uniform pressure of 1448 kPa (210 lbf/in.²) applied over six rectangular areas of 0.145 m² (1.56 ft²) each (see Figure 1). These areas were placed at two axle spacings of 1448 mm (57 in.) and a dual spacing of 1397 mm (55 in.), which is the geometry of the Boeing B-777 aircraft (see Figure 1). The position of the tri-tandem gear loading was varied among seven locations along the x -direction and nine different locations along the y -direction [a total of 63 locations with load center coordinates x/L and y/L , $L = 7.62$ m (25 ft)] in the lower-left pavement slab (see Table 1). The load locations chosen in both x - and y -axes were determined according to the results of an extensive study, which investigated the effects of load location on

TABLE 1 Values of Six Input Parameters Used in ILLI-SLAB Analyses

	Location of the center of the gear relative to the center of the four-slab assembly		Slab thickness, T		Modulus of subgrade reaction, k		Load Transfer Efficiencies, (LTEs)	
	x/L	y/L	(mm)	(in.)	(MPa/m)	(psi/in.)	LTE-x	LTE-y
Training	0.217	0.115	305	12.0	13.6	50	25	25
	0.244	0.138	381	15.0	20.4	75	60	60
	0.271	0.160	457	18.0	33.9	125	80	80
	0.325	0.183	533	21.0	47.5	175	90	90
	0.380	0.229	610	24.0	74.7	275		
	0.434	0.275			101.8	375		
	0.516	0.344			135.7	500		
		0.413						
Testing	0.299	0.206	330	13.0	16.3	60	45	45
	0.353	0.252	406	16.0	27.1	100	70	70
	0.407	0.298	482	19.0	40.7	150	85	85
	0.461	0.367	558	22.0	61.1	225		
		0.458			122.2	450		

the trained ANN model accuracy. Applying symmetry along both x - and y -directions, these locations effectively covered a representative area for all possible tri-tandem gear-loading positions on the four-slab assembly.

To maintain the same level of accuracy in the results from all analyses, a standard ILLI-SLAB finite element mesh was constructed for the lower-left loaded slab. This mesh consisted of 1,554 elements with 38 nodes used in the x -direction at a standard spacing of 206.8 mm (8.15 in.) and 43 nodes used in the y -direction at a standard spacing of 174.6 mm (6.875 in.) (see Figure 1). This mesh was reported previously to give a high level of accuracy when predicted stresses due to single wheel loading were compared with the analytical solutions (17). The location of the Boeing B-777 gear loading on the mesh was also of primary importance to obtain accurate and consistent results for maximum slab stresses and deflections. Both the corners and the centerpoint of each loaded square had to coincide at all times with the node points in the finite element mesh (see Figure 1).

At the end of each analysis, the maximum bending stresses (σ_x -max and σ_y -max) and the maximum vertical deflections (δ -max), due to the applied loading were calculated on the pavement section. Although the maximum bending stresses in the y -direction varied from 352 kPa (51 lbf/in.²) to 8230 kPa (1,194 lbf/in.²), the maximum bending stresses in the x -direction changed from 668 kPa (97 lbf/in.²) to 7380 kPa (1,070 lbf/in.²). The maximum deflections ranged from 0.4 mm (0.015 in.) to 11.2 mm (0.44 in.). The maximum stresses generally were found directly under the center of one wheel, except for the edge loading condition of the slab, in which case the maximum stresses were found at the slab edges. After each analysis was complete, the input variables for load location (x/L and y/L), slab thickness (t), modulus of subgrade reaction (k), and LTEs were recorded, along with the output maximum bending stresses and maximum deflections. Finally, a training database was formed by using the 35,280 data set comprising both the input variables and the output responses from all analyses.

An independent testing database also was required during training to verify the prediction ability of the various ANN models. For this purpose, 3,600 additional ILLI-SLAB runs were generated by using new input parameters. The new input values selected were completely different from, but within the ranges of, those used for training of the ANN model (see Table 1). Since ANNs learn relations and approximate functional mapping limited by the extent of the training data, the best use of the trained ANN models can be achieved in interpolation. The maximum bending stresses and deflections corresponding to the new independent testing data set were then calculated by using the ILLI-SLAB program, and then they were compared to the output stresses and deflections obtained by using the ANN model.

NEURAL NETWORK TRAINING AND VALIDATION

To train a backpropagation neural network with the results of the finite element analyses, a network architecture was required. Six input variables (x/L , y/L , t , k , LTE- x , and LTE- y) were used in the network input layer. The three output variables were the maximum bending stresses (σ_x -max and σ_y -max) and the maximum vertical deflection (δ -max) in the pavement section. A network with two hidden layers was chosen exclusively for the ANN models trained in this study. Satisfactory results were obtained in the previous studies with these types of networks because of their ability to better facilitate the nonlinear functional mapping with the use of relatively fewer neurons (7,18). The backpropagation ANN program Backprop 3.5, developed by Meier (19), was used for the training process, which consisted of iteratively presenting training examples to the network. The neural network sigmoidal transfer function could output results only within the range of 0 and 1 (13). Haykin (15) suggested that offsetting the target values away from the limits of the sigmoidal activation function increases the learning process. Both the 35,280 training and the 3,600 independent testing data sets, therefore, were normalized between the values of 0.1 and 0.9. Each training "epoch" of the network consisted of one pass over the entire 35,280 data set. The 3,600 independent testing data sets were used to monitor the training progress, for a total of 10,000 epochs, which was found to be sufficient for proper network training. The function mapping and approximation ability of the trained ANN model was verified for each of the maximum stresses and maximum deflections with the low testing and training mean squared error (MSE) values.

Twenty-one network architectures with two hidden layers were trained for predicting the two maximum bending stresses and maximum deflections with six input nodes and three output nodes. Figure 2 compares the training and testing MSEs of the maximum x -stress (σ_x -max), maximum y -stress (σ_y -max), and maximum deflection (δ -max) obtained for each network architecture at the end of 10,000 training epochs. Overall, the MSEs decreased as the networks grew in size with increasing number of neurons in the hidden layers. The testing MSEs for the two stresses and deflections were in general lower than the training ones. The error levels for both training and testing sets matched closely when the 6-29-29-3 network architecture was approached (6 input, 29 and 29 hidden, and 3 output neurons, respectively). The lowest training MSEs in the order of 1×10^{-6} (corresponding to a root MSE of 0.1 percent) were obtained with the 6-29-29-3 architecture for both the x - and y -stresses. The MSE magnitudes of both training and testing were the lowest for the maximum deflections. This is in good agreement with the results of

FIGURE 2 Performance of various ANN architectures at end of 10,000 training epochs.

the finite element analyses, because the deflections are computed first and then the stresses are derived from the deflections. Networks much larger than 29 neurons (40 neurons) in two hidden layers, not shown in Figure 2, were tested and did not significantly improve the error levels.

The 6-29-29-3 architecture was chosen as the best architecture for the ANN model based on its lowest training and independent testing MSEs. The computed average errors and the maximum individual errors were in most cases the lowest, as tabulated in Table 2. It

is important to realize that performance of a network depends on the initial values of the node weights, which are selected at random. This may explain the few error spikes observed in Figure 2. Figure 3 shows the training and testing MSE progress curves for the 6-29-29-3 network. Both the training and testing curves for each of the three outputs are approximately in the same order of magnitude, thus depicting proper training. The testing MSEs in general were slightly lower than the training ones, possibly because of the 3,600 testing data sets being sampled from low-stress concentration load loca-

TABLE 2 Average and Maximum Individual Errors for Different Network Architectures

Network Architecture	Average Error						Maximum Individual Error					
	σ_x		σ_y		δ_v		σ_x		σ_y		δ_v	
	(kPa)	(%)	(kPa)	(%)	(μm)	(%)	(kPa)	(%)	(kPa)	(%)	(μm)	(%)
6-10-10-3	25.9	1.2	24.0	0.9	16.58	1.3	125.0	5.7	153.6	3.4	102.8	3.7
6-11-11-3	31.0	1.5	23.1	0.9	20.71	1.6	141.8	5.3	108.3	2.3	117.7	3.3
6-12-12-3	23.3	1.1	20.7	0.8	16.92	1.4	94.0	2.9	124.1	2.8	101.4	4.2
6-13-13-3	20.4	1.0	19.9	0.7	15.92	1.2	98.2	4.4	132.9	2.9	101.4	4.0
6-14-14-3	14.7	0.7	20.6	0.8	13.02	1.1	85.6	4.1	160.5	3.5	93.3	2.6
6-15-15-3	19.2	0.9	15.8	0.6	15.07	1.1	104.0	3.1	112.3	2.4	94.7	2.7
6-16-16-3	16.3	0.8	19.2	0.8	14.44	1.1	83.9	3.2	90.6	2.9	92.0	2.7
6-17-17-3	12.2	0.6	16.7	0.7	11.04	0.8	66.3	2.0	81.7	2.1	77.1	3.3
6-18-18-3	15.7	0.7	16.4	0.6	13.61	1.1	73.0	2.9	89.6	2.0	73.0	3.1
6-19-19-3	15.6	0.7	11.5	0.4	11.16	0.8	72.1	2.2	71.9	1.6	98.7	4.1
6-20-20-3	11.2	0.5	14.0	0.5	8.28	0.6	78.0	3.1	74.8	2.4	82.5	3.4
6-21-22-3	11.6	0.5	13.5	0.5	8.81	0.6	66.3	2.6	74.8	1.6	58.2	2.5
6-22-22-3	11.2	0.5	10.8	0.4	8.48	0.7	64.6	2.6	62.0	2.0	51.4	2.4
6-23-23-3	12.4	0.6	14.3	0.6	8.57	0.7	67.1	2.6	67.0	1.5	66.3	2.8
6-24-24-3	10.9	0.5	9.8	0.4	7.57	0.6	67.1	3.2	58.1	1.3	43.3	1.9
6-25-25-3	9.4	0.4	14.5	0.6	7.15	0.5	61.2	2.4	60.1	1.3	71.7	3.0
6-26-26-3	12.3	0.6	9.9	0.4	8.92	0.7	61.2	1.8	52.2	1.1	56.8	1.9
6-27-27-3	8.3	0.4	9.5	0.4	9.32	0.7	55.4	2.2	57.1	1.2	41.9	1.3
6-28-28-3	9.1	0.4	10.9	0.4	9.37	0.8	67.1	2.6	83.7	1.8	51.4	1.5
6-29-29-3	9.0	0.4	9.6	0.4	6.56	0.5	53.7	2.1	38.4	1.6	47.3	1.9
6-30-30-3	9.6	0.4	12.1	0.5	7.04	0.5	79.7	3.1	56.1	1.2	50.0	2.1

Note: 1 psi = 6.89 kPa

FIGURE 3 Training progress of 6-29-29-3 network.

tions. In addition, the training MSE curves were smoother than the testing ones, displaying no error spikes. The almost constant MSEs obtained for the last 5,000 epochs (see Figure 3) also provided a good indication of adequate training for this network.

Figures 4(a) and 4(b) compare the predicted maximum ANN stresses in x - and y -directions, respectively, with the finite element results. The average error for the maximum stress in the x -direction was ± 9 kPa (1.3 lbf/in.²) (i.e., ± 0.4 percent), while the average error in the y -direction was ± 9.6 kPa (1.4 lbf/in.²) (i.e., ± 0.4 percent). These average errors were calculated as the sum of the individual errors divided by 3,600. The maximum individual error for the stress in x -direction was ± 53.7 kPa (7.8 lbf/in.²) (i.e., ± 2.1 percent) for an actual stress magnitude of 2544 kPa (366 lbf/in.²), while the maximum individual error for the stress in y -direction was ± 38.4 kPa (5.6 lbf/in.²) (i.e., ± 1.6 percent) for an actual stress magnitude of 2473 kPa (359 lbf/in.²). Both the individual maximum errors predicted for x - and y -stresses occurred at mid-edge loading. This was expected because the magnitudes of predicted stresses and the stress gradients considerably increase, especially in the case of near-edge loading conditions, which was also observed by Ceylan et al. (7) and Haussmann et al. (18).

Figure 4(c) compares the predicted maximum ANN deflections with the results of the ILLI-SLAB finite element program. The average error for the predicted maximum vertical deflections was ± 0.5 percent (6.6 μ m), while the maximum individual error was ± 1.9 percent (0.046 mm), for an actual deflection of 2.52 mm (0.1 in.). Maximum errors occurred close to the slab corners, where maximum deflections were computed. Average errors were the lowest for the 6-29-29-3 network when compared to the other networks analyzed (see Table 2).

The 6-29-29-3 ANN model was deemed to have achieved its goal and performed superiorly by literally enabling quick prediction of the ILLI-SLAB stresses and deflections on the standard concrete slab under the tri-tandem gear loading. As mentioned, the results from the ILLI-SLAB model have been tested extensively by comparison of results with available theoretical solutions and experimental studies (5,6). Therefore, the feasibility of using an ANN model as a design toolbox for facilitating the results of finite element analyses on various loading conditions appears to be very promising and is being pursued within the scope of this study.

The most important benefit of the ANN model is that it does not require any complicated and time-consuming finite element input file preparation for routine design applications. Also, it provides a considerable reduction in the calculation time needed for each analysis. The actual ILLI-SLAB computation time for each analysis in this study took approximately 35 seconds on a PC computer with a 200 MHz Pentium processor and 64 MB of RAM. In contrast, the ANN model requires no complicated input file construction after the network is trained; even old model, low-end computers can be used to predict the stresses and deflections practically in less than 1 second, and there is no need for an extra step to obtain the output stresses and deflections, i.e., the postprocessing of the output file. For a large number of analyses to be performed, the time saved by using the ANN model can be invaluable to the pavement engineer when making "what if" comparisons of pavement systems.

SENSITIVITY ANALYSIS OF ANN MODEL PREDICTIONS

The training input variables, that is, the load coordinates on the slab (x/L and y/L), slab thickness (t), the modulus of subgrade reaction (k), and the load transfer efficiencies (LTE- x and LTE- y) had to be extensively studied and researched for obtaining the excellent performance from the ANN models. The best performing 6-29-29-3 ANN model then supposedly captured within its network connections the functional relations between those critical inputs (x/L , y/L , t , k , and LTEs) and the predicted output responses. How effective those selected input values were for improving the training and function approximation is investigated in this section by further testing the prediction capabilities of the 6-29-29-3 network with different input queries.

In the first analysis, sensitivity of the ANN predicted maximum stresses to load location was studied by varying individually each of the load coordinates x/L and y/L . The slab thickness, the modulus of subgrade reaction, and the load transfer efficiencies were held constant at 305 mm (12 in.), 13.6 MPa/m (50 lbf/in.²/in.), and 25 percent, respectively. Figure 5 shows the variations of the predicted stresses (σ_x -max and σ_y -max) with load location when (1) $x/L = 0.217$ was kept constant and y/L values were queried for 0.17, 0.321, 0.39, and 0.481, and when (2) $y/L = 0.115$ was kept constant and x/L values were queried for 0.26, 0.31, 0.42, and 0.49. In addition, also shown in Figure 5 are the stresses predicted in the slab at training and testing load locations for these x/L (or y/L), used for training and testing of the ANN model (see Table 1). The load locations selected, therefore, corresponded to a complete range of values along each of the x - and y -directions, which were used to analyze in detail the near-edge slab loading conditions.

When $y/L = 0.115$ was kept constant and x/L was varied from 0.217 to 0.516, maximum x -stress increased in a piecewise continuous functional form, whereas the maximum y -stress first decreased steeply and then smoothly increased. The opposite occurred when

(a)

(b)

(c)

FIGURE 4 Accuracy of 6-29-29-3 network for predicting maximum bending stresses (a) in x -direction and (b) in y -direction and (c) for predicting maximum vertical deflections.

$x/L = 0.217$ was kept constant and y/L was varied from 0.115 to 0.504: the x -stress decreased first and remained almost constant, whereas the y -stress continuously increased. As the load coordinate x/L or y/L increases from edge to center, the maximum stresses predicted smoothly change in a piecewise continuous functional form. This suggests that the ANN model then sufficiently generalized the load location input parameters used in the training data.

Figure 6 shows both variations of maximum stresses with slab thickness, t , and modulus of subgrade reaction, k . The coordinates of the load location (x/L , y/L), the modulus of subgrade reaction (k), and LTEs were held constant at (0.516, 0.115), 13.6 MPa/m, and 25 percent, respectively. To further validate the prediction ability of the ANN model, four new queries were made for the following additional slab thicknesses: 355.6 mm (14 in.), 431.8 mm (17 in.), 508 mm (20 in.), and 584.2 mm (23 in.). Figure 6(a) shows the variations of the predicted maximum x - and y -stresses for slab thicknesses of

304.8 mm (12 in.) to 609.6 mm (24 in.) used for training, testing, and validation. Because of the selected load location, $x/L = 0.516$ and $y/L = 0.115$, and the orientation of the tri-tandem gear loading, the predicted maximum x -stresses are much larger than the y -stresses. Nevertheless, there is a significant reduction (almost threefold) for both the x - and y -stresses with increasing slab thickness.

Figure 6(b) shows the effects of increasing modulus of subgrade reaction (k) on the predicted maximum stresses studied for k values varying from 13.6 MPa/m to 135.7 MPa/m (500 lbf/in.²/in.). This time, the coordinates of the load location (x/L , y/L), the slab thickness (t), and the load transfer efficiencies (LTE- x , LTE- y) were held constant at (0.516, 0.115), 304.8 mm, and 25 percent, respectively. Five additional k values—24.4 MPa/m (90 lbf/in.²/in.), 54.3 MPa/m (200 lbf/in.²/in.), 67.9 MPa/m (250 lbf/in.²/in.), 88.2 MPa/m (325 lbf/in.²/in.), and 128.9 MPa/m (475 lbf/in.²/in.)—were selected as new queries and used in the sensitivity study. Although the x -stresses

FIGURE 5 Variation of maximum stresses with load location.

(a)

(b)

FIGURE 6 Variation of maximum stresses with (a) slab thickness and (b) modulus of subgrade reaction.

tend to decrease significantly with increasing subgrade support k values, for all practical purposes, the y -stresses remain constant and are not affected by changing subgrade stiffness for the specific load location, $x/L = 0.516$ and $y/L = 0.115$. Once again, the predicted stresses for the five new k values exactly fell on the piecewise smooth curve obtained by the trained ANN model.

Finally, the effects of LTEs on the predicted maximum bending stresses were analyzed by varying LTE values from 25 percent to 90 percent for two load locations, A and B (see Figure 7). For this analysis, slab thickness (t) and modulus of subgrade reaction (k) were held constant at 304.8 mm and 13.6 MPa/m, respectively. Figure 7 shows the variations of the predicted stresses (σ_x -max and σ_y -max) with LTEs when (a) LTE- $x = 25$ percent was kept constant and LTE- y values were queried for 35 percent, 50 percent, and 75 percent; and (b) LTE- $y = 25$ percent was kept constant and LTE- x values were queried for 35 percent, 50 percent, and 75 percent. Similar to previous illustrations, the bending stresses predicted from training and testing of the ANN model are shown in Figure 7, together with the new query results. As can be seen in Figure 7, when LTE- $x = 25$ percent is kept constant and LTE- y is varied from 25 percent to 90 percent, maximum y -stresses increase in a piecewise continuous functional form, whereas the maximum x -stresses smoothly decrease. On the other hand, the opposite occurs when LTE- $y = 25$ percent is kept constant and LTE- x is varied from 25 percent to 90 percent, i.e., maximum x -stresses increase in a piecewise continuous functional form, whereas the maximum y -stresses smoothly decrease.

The 6-29-29-3 ANN model, therefore, successfully interpolates the predicted results for the various training input variables, that is, the load coordinates on the slab (x/L and y/L), slab thickness (t), the modulus of subgrade reaction (k), and the LTEs. Without being constrained by prior assumptions of the functional form of the relationships, the trained ANN model has captured the nonlinear relations between the maximum stresses and deflections and the critical input variables. The prediction capability of the network appears to be accurate, as illustrated by the excellent match between the validation stresses on the piecewise smooth functional relations indicated in Figures 5, 6, and 7.

FIGURE 7 Variation of maximum bending stresses with deflection load transfer efficiencies.

SUMMARY AND CONCLUSIONS

1. In jointed concrete airfield pavements, maximum bending stresses and deflections calculated under the wheel load vary considerably, depending on the load location on the slab, the joint LTEs, the slab thickness, and the subgrade support. The use of ANNs as analysis design tools is demonstrated in this paper by analyzing concrete airfield pavements serving the Boeing B-777 aircraft.

2. An ANN model was successfully trained with the results of more than 38,000 ILLI-SLAB finite element analyses runs performed on a four-slab airfield pavement system. Under the six-wheel tri-tandem type B-777 gear loading, the ANN model predicted maximum stresses and deflections with average errors less than 0.5 percent when compared with those computed by the ILLI-SLAB.

3. The prediction capability of the ANN model appears to be accurate when predicting maximum stresses and deflections for various load locations, slab thicknesses, subgrade supports and the joint load transfer efficiencies matched exactly on the piecewise continuous functional relations obtained from training of the model.

4. The use of the ANN model resulted in both a drastic reduction in computation time and a simplification of input and output requirements over the finite element program that are currently needed for routine practical design. The application of an ANN model to predict the results of finite element analyses, therefore, proved to be very promising.

5. Current research focuses on the expansion of the ANN model to handle all possible aircraft gear configurations with multiple-wheel loading conditions by the use of the superposition principle.

ACKNOWLEDGMENTS

This paper was prepared from a study conducted at the Center of Excellence for Airport Pavement Research. Patricia Watts is the FAA program manager for Air Transportation Centers of Excellence and Satish Agrawal is the FAA technical director for the pavement center. Funding for this paper was provided by a Paul F. Kent Endowment to the University of Illinois at Urbana-Champaign.

REFERENCES

1. *Research and Development of the Asphalt Institute's Thickness Design Manual (MS-1)*, 9th ed. Research Report 82-2. Asphalt Institute, 1982.
2. Claussen, A. I. M., J. M. Edwards, P. Sommer, and P. Uge. Asphalt Pavement Design—The Shell Method. *Proc., Fourth International Conference on the Structural Design of Asphalt Pavements*. Vol. 1. 1977, pp. 39–74.
3. *Airport Pavement Design for the Boeing 777 Airplane*. Advisory Circular 150/5320-16. FAA, U.S. Department of Transportation, Washington, D.C., 1995.
4. Tabatabaie-Raissi, A. M. *Structural Analysis of Concrete Pavement Joints*. Ph.D. thesis. University of Illinois, Urbana, 1977.
5. Tabatabaie, A. M., and E. J. Barenberg. Finite-Element Analysis of Jointed or Cracked Concrete Pavements. In *Transportation Research Record 671*, TRB, National Research Council, Washington, D.C., 1978, pp. 11–19.
6. Tabatabaie, A. M., and E. J. Barenberg. Structural Analysis of Concrete Pavement Systems. *Transportation Engineering Journal*, Vol. 106, No. TE5, 1980.
7. Ceylan, H., E. Tutumluer, and E. J. Barenberg. Artificial Neural Networks as Design Tools in Concrete Airfield Pavement Design. *ASCE International Air Transportation Conference*, Austin, Texas, 1998, pp. 447–465.
8. Timoshenko, S., and S. Woinowsky-Krieger. *Theory of Plates and Shells*, 2nd ed. McGraw-Hill, New York, 1959.
9. Tabatabaie, A. M., E. J. Barenberg, and R. E. Smith. *Longitudinal Joint Systems in Slip-Formed Rigid Pavements, Vol. II—Analysis of Load Transfer Systems for Concrete Pavements*. Report FAA-RD-79-4. U.S. Department of Transportation, 1979.
10. Thompson, M. R., A. M. Ioannides, E. J. Barenberg, and J. A. Fischer. *Development of a Stress Dependent Finite Element Slab Model*. Report TR-83-1061. U.S. Air Force Office of Scientific Research, Air Force Systems Command, Bolling Air Force Base, Washington, D.C., 1983.
11. Werbos, P. *Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences*. Ph.D. dissertation. Harvard University, Cambridge, Mass., 1974.
12. Parker, D. B. *Learning Logic*. Technical Report TR-47. Center for Computational Research in Economics and Management Science, Massachusetts Institute of Technology, Cambridge, Mass., 1985.
13. Rumelhart, D. E., G. E. Hinton, and R. J. Williams. Learning Representations by Back-Propagating Errors. *Nature*, Vol. 323, 1986, pp. 533–536.
14. Hecht-Nielsen, R. *Neurocomputing*. Addison-Wesley, New York, 1990.
15. Haykin, S. *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Inc., Englewood Cliffs, N.J., 1994.
16. Meier, R., and E. Tutumluer. Uses of Artificial Neural Networks in the Mechanistic-Empirical Design of Flexible Pavements. *Proc., International Workshop on Artificial Intelligence and Mathematical Methods in Pavement and Geomechanical Engineering Systems*. Florida International University, Florida, 1998, pp. 1–12.
17. Korovesis, G. T. *Analysis of Slab-on-Grade Pavement Systems Subjected to Wheel and Temperature Loadings*. Ph.D. dissertation. University of Illinois at Urbana-Champaign, Urbana, Ill., 1990.
18. Haussmann, L. D., E. Tutumluer, and E. J. Barenberg. Neural Network Algorithms for the Correction of Concrete Slab Stresses from Linear Elastic Layered Programs. In *Transportation Research Record 1568*, TRB, National Research Council, Washington, D.C., 1997, pp. 44–51.
19. Meier, R. W. *Backcalculation of Flexible Pavement Moduli from Falling Weight Deflectometer Data Using Artificial Neural Networks*. Ph.D. dissertation. Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, 1995.

The contents of this paper reflect the views of the authors, who are responsible for the facts and accuracy of the data presented. The contents do not necessarily reflect the official views and policies of the FAA. This paper does not constitute a standard, specification, or regulation.

Publication of this paper sponsored by Committee on Rigid Pavement Design.