A Neural Network Approach for Mechanistic Analysis of Jointed Concrete Pavement

Ghassan ABU-LEBDEH[a], Kamran AHMED[b]

[a]*American University of Sharjah, Sharjah, United Arab Emirates*
[a]*Email: gabulebdeh@aus.edu*
[b]*United Arab Emirates University, Al-Ain, United Arab Emirates*
[b]*Email: ahmedka@uaeu.ac.ae*

Abstract: A complete factorial analysis of 9072 combinations of jointed concrete pavement design inputs was initiated with some modifications of the experimental matrix applied to represent all design practice of a typical department of transport in the Snowbelt region of the US. Several axle and truck configurations frequently observed in the state were considered in the analysis by placing the load configuration at the location that results in the maximum response, so-called critical load location. Mechanistic responses were obtained through finite element analysis using ISLAB2000® structural model. These mechanistic responses were used to train, test and validate a neural network model. The neural network-based model was then used to provide a full catalog of mechanistic responses that were not addressed in the final experimental matrix. The results show high coefficient of correlation (R^2) for both testing and validation data, which proved the model's generalization ability-- a critical indicator of the goodness of the models since these data sets were not used in the model development (i.e., during the training stage)—and, hence, utility to assess different types of pavement designs and loadings.

Keywords: Concrete pavement, neural networks, mechanistic response

1. PROBLEM STATEMENT

ISLAB2000® structural model is a finite element program for the analysis of jointed concrete pavements. The input values used by ISLAB2000® are Axle Type, Joint Spacing, Shoulder Type, PCC Thickness, Base Thickness, K value and Temperature as shown in table 1. If one is to analyze the data range shown in table 1 for seven inputs then ISLAB2000® will need approximately four hundred and eighty thousand combinations, which is time consuming and impractical in real world applications. To overcome this problem, neural network-based approach is proposed in this study. Nine thousand and seventy two combinations were taken from ISLAB2000® model where half of them were used to train the network and the remaining data was used to test and validate the neural network model.

Table 1. Input variables used to predict stresses

Input Variables	Values or Ranges	Format
Axle Type	Single, Tandem, Tridem, more than 4 Axles	Discrete
Joint Spacing	177,315	Continuous
Shoulder Type	PCC, AC, Widened Lane	Discrete
PCC Thickness	6, 7,8,9,10,11,12	Continuous
Base Thickness	4,16,26	Continuous
K value	30,100,200	Continuous
Temperature	0,10,20	Continuous

2. LITERATURE REVIEW

Neural networks have been used extensively in pavement design and performance evaluation (among many others: Bayrak & Ceylan, 2008; Ceylan et al., 1998; Ferregut & Abdalla, 1998; Pekan et al., 2008; Poole et al., 1998; Saltan & Terzi, 2004; Suleiman et al., 20011). For example, Farregut et al (1998) used neural network back propagation to predict longitudinal roughness of pavement. They used 157 sections to develop the neural network model of the International Roughness Index (IRI). Out of the 157 they used 140 sections to train the network and 17 sections to validate the network. They found high correlation coefficient value (R^2) for the training and validation data models. Fontul et al. (2003) developed a neural network model for structural evaluation of pavements. The Falling Weight Deflectometer (FWD) database was used as input to the neural network. Training was performed with 1000 datasets randomly chosen from 26000 data points. Validation was done using data in the same range as the training but which was not actually used during the training stage. The neural network models showed good results for the structural pavement evaluation. However, other models and procedure may be used to study jointed concrete pavements. For example, Seo and Kim (2013) studies longitudinal cracking at transvers joints in jointed pavements and developed models using finite element modeling.

3. ARTIFICIAL NEURAL NETWORK

3.1 Background

An artificial neural network (ANN) is composed of number of interconnected units, which has a natural tendency for storing experiential knowledge and making it available for use. ANN is a branch of the more general field of Artificial Intelligence (AI). AI theory aims at study and design of intelligent systems where an intelligent system is one that perceives its environment and takes actions that maximize its chances of success.

ANNs can be used to approximate some complex input-output relationship and have proved to be powerful tools for function approximation. They are usually fed with a large amount of data to approximate the underlying relationship. The organization of the neurons and weight of the connections determine the output in response to an external input stimulus.

3.2 Neural Network Model

In this study, feed forward back propagation (FFBP) type neural network was trained, tested and validated using the MATLAB (MATrix LABoratory) Neural Network Toolbox version 4. FFBP is a powerful network which can be taught to map one data into another using the "examples" for the mapping to be learned. The architecture of a simple FFBP is a collection of nodes distributed over an input layer, hidden layer(or layers) and an output layer as shown in figure 1. The nodes between successive layers are connected with links, each of which carries a weight that describes the strength of that connection. The connection weights are initially selected at random. The errors between outputs and the actual answers (or targets) are then propagated backward through the network and the connection weights are individually adjusted so as to reduce the error. The examples to develop a FFBP neural network model were obtained from a finite element program.

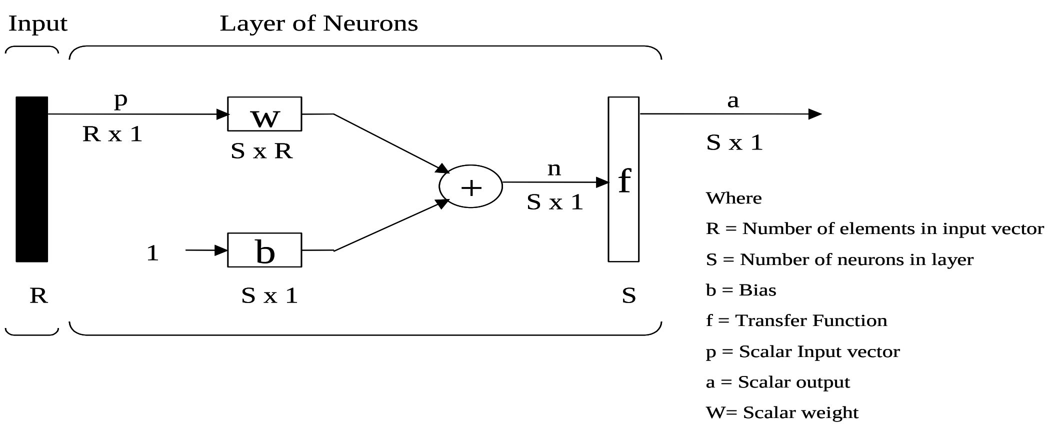


Figure 1. Basic architecture of Feed Forward Back Propagation Neural Network

4. EXPERIMENTAL SETUP

An ANN model was trained for this research with the results from the ISLAB2000 finite element program**.** Longitudinal bottom, transverse bottom and longitudinal top stresses were predicted on the basis of Axle Type, Joint Spacing, Shoulder Type, PCC Thickness, Base Thickness, K value and Temperature. Table 1 shows the inputs variable ranges with their data structure.

Nine thousand seventy two mechanistic responses were obtained using ISLAB2000 based on the finalized experimental matrix. Table 2 shows the total number of data points available for each input variable. The matrix did not capture all possible combinations. However, this database can be used to develop a neural network model that will suitably predict pavement response for all possible variables.

Table 2. Total Numbers of Data Points for Each Input Variable

Input Variables		Available Data Points
Axle Type	Single Axle	1134
	Tandem	1134
	Tridem	1134
	Multi Axle	5670
Joint Spacing	177 inches	4536
	315 inches	4536
PCC Thickness	6 inches	1296
	7 inches	1296
	inches	1296
	9 inches	1296
	10 inches	1296
	11 inches	1296
	12 inches	1296
Base Thickness	4 inches	3024
	16 inches	3024
	26 inches	3024
K Value	30 psi/in	3024
	100 psi/in	3024
	200 psi/in	3024
Temperature Gradient	0	3024
	10	3024
	20	3024
Lateral Support	PCC	3024
	AC	3024
	Widened with AC Shoulder	3024

5. DATA FOR TRAINING, VALIDATION AND TESTING

To improve the generalization ability of the network and to avoid over-training (that is when the network actually memorizes data and patterns), "Early Stopping" technique was used. In this technique the available data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error in the validation set is monitored (not used in computing or updating weights) during the training process. In the initial phase of training, the error of validation decrease with more training data. However when the network begins to over-fit the data to the model, the error in the validation set starts increasing. When the validation error increases for a specified number of successive iterations, the training is stopped and the weights and biases at the minimum of the validation error are retained. The test set error is not used during the training, but it is used to compare different models (Matlab, 2003). In our case, we had 9072 data points, used 50% (4536) for training, 25% (2268) were used for for validation, and the remaining 25% were used for testing.

5.1 Pre and Post processing of Data

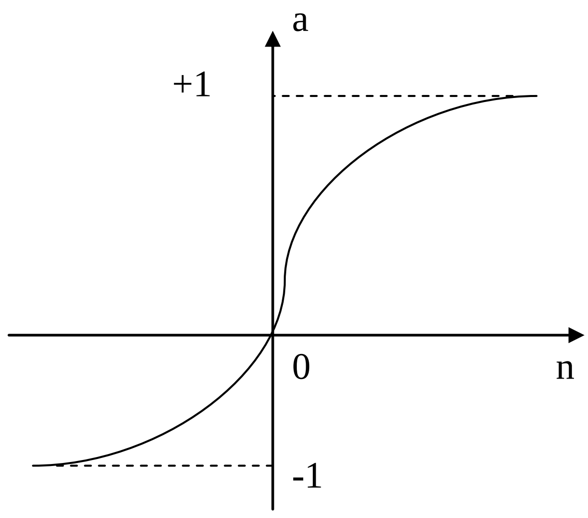
The seven inputs and three targets were preprocessed before starting the training process. Neural network training becomes more efficient by preprocessing the inputs and targets. The function "Premnmx" was used to preprocessed the data, which scaled both the inputs and targets in the range [-1,1]. The outputs produced by the network were also in the same range, which were converted into original units by using the function "Postmnmx". Following algorithm was used to pre and post processing.

$$\text{pn} = \frac{2\times(\text{p-minp})}{(\text{maxp - minp})} - 1$$

Where
p = Original Input or Target value
pn = Value of Input or Target in the range of [-1,1]

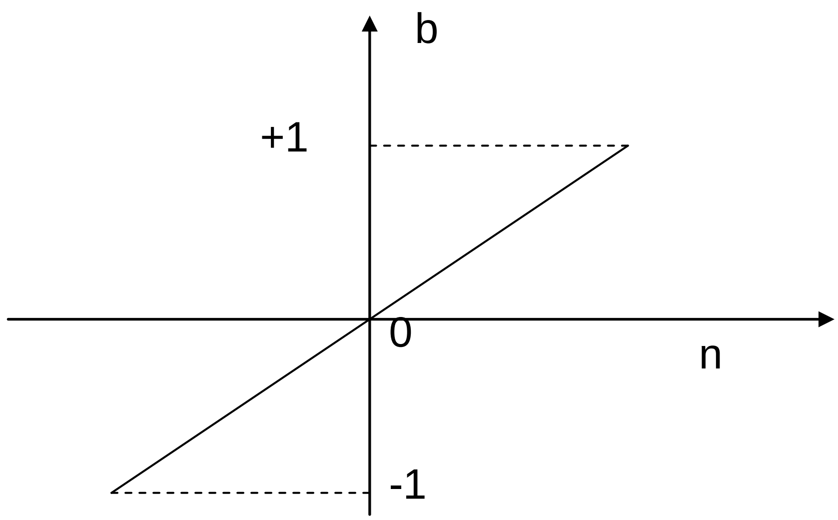
5.2 Transfer Function

There is a number of transfer functions available in the Matlab neural network tool box including Saturating linear transfer function (satlin), Log sigmoid transfer function (logsig), Hyperbolic tangent sigmoid transfer function (tansig) etc (Matlab, 2003). The selection of any transfer function depends upon the data range. For example in our case we normalized the training data by preprocessing data to fit in the range of [-1,1]. We selected two types of transfer functions, the Pureline and Tansig. The properties of these transfer function are shown in figure 2 and 3.



a = tansig (n)

Figure 2. Tan-Sigmoid Transfer Function



b = Purelin (n)

Figure 3. Pure-line Transfer Function

6. NEURAL NETWORK ARCHITECTURE

The feed forward back propagation (FFBP) type neural network model was used to train the network. Figure 4 shows the architecture of the FFBP neural network model used with the inputs and targets. There is one rule to decide the number of hidden neurons and layers; using large number of neurons saturates the network and the network starts memorizing the targets without getting the logic. By using the Early stopping technique this problem can be eliminated. To make the network less complicated and more generalized, different number of hidden neurons was tried. The optimal network was selected on the basis of the least mean square error. Figure 5 and 6 shows the mean-square errors and the properties of different combinations tried for the two-layer and three-layer models, respectively.

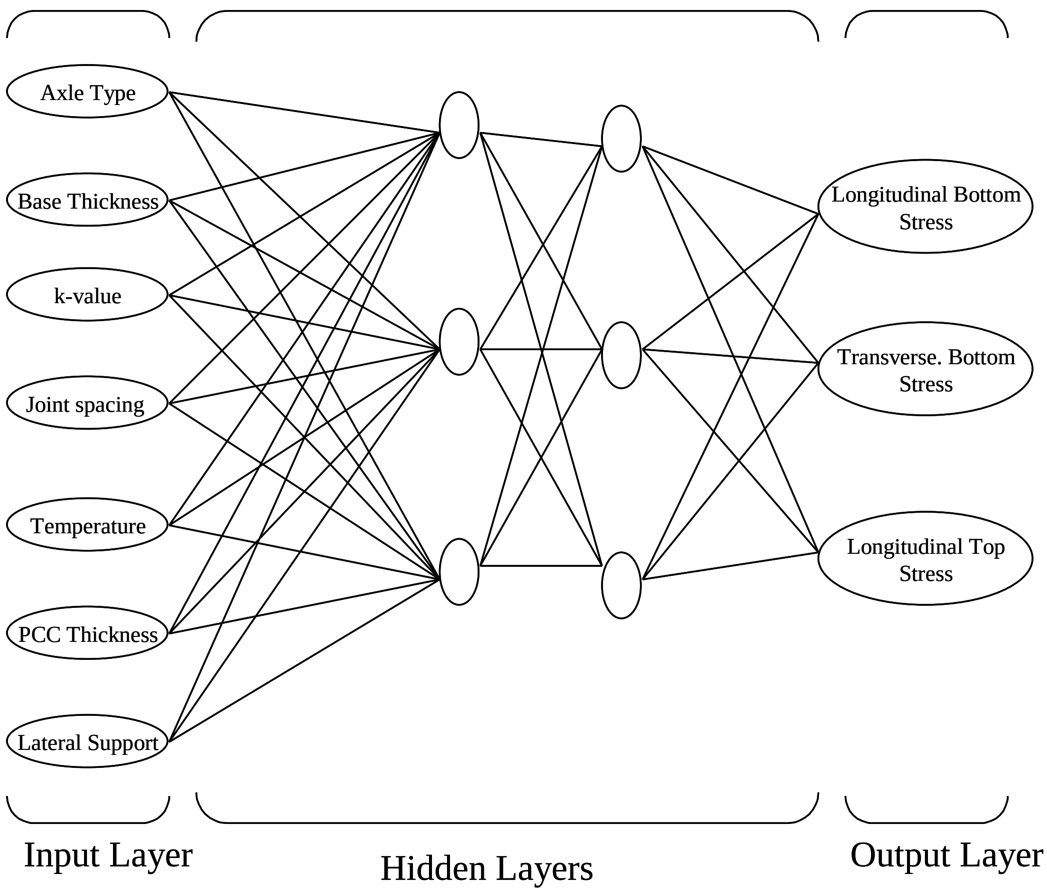


Figure 4. Feed Forward Back Propagation neural network with seven inputs and three targets.

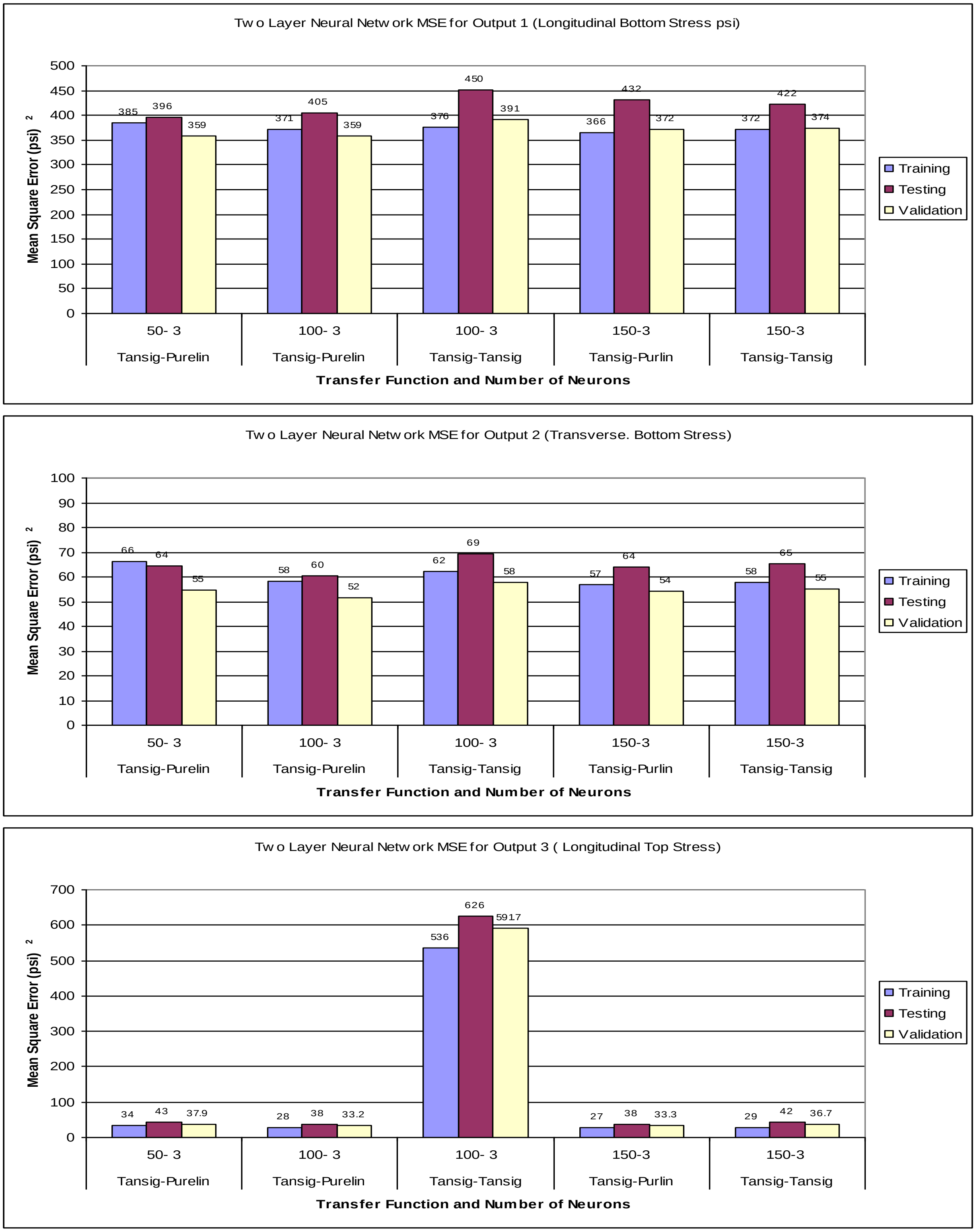


Figure 5. Mean squares for the two layer neural network models

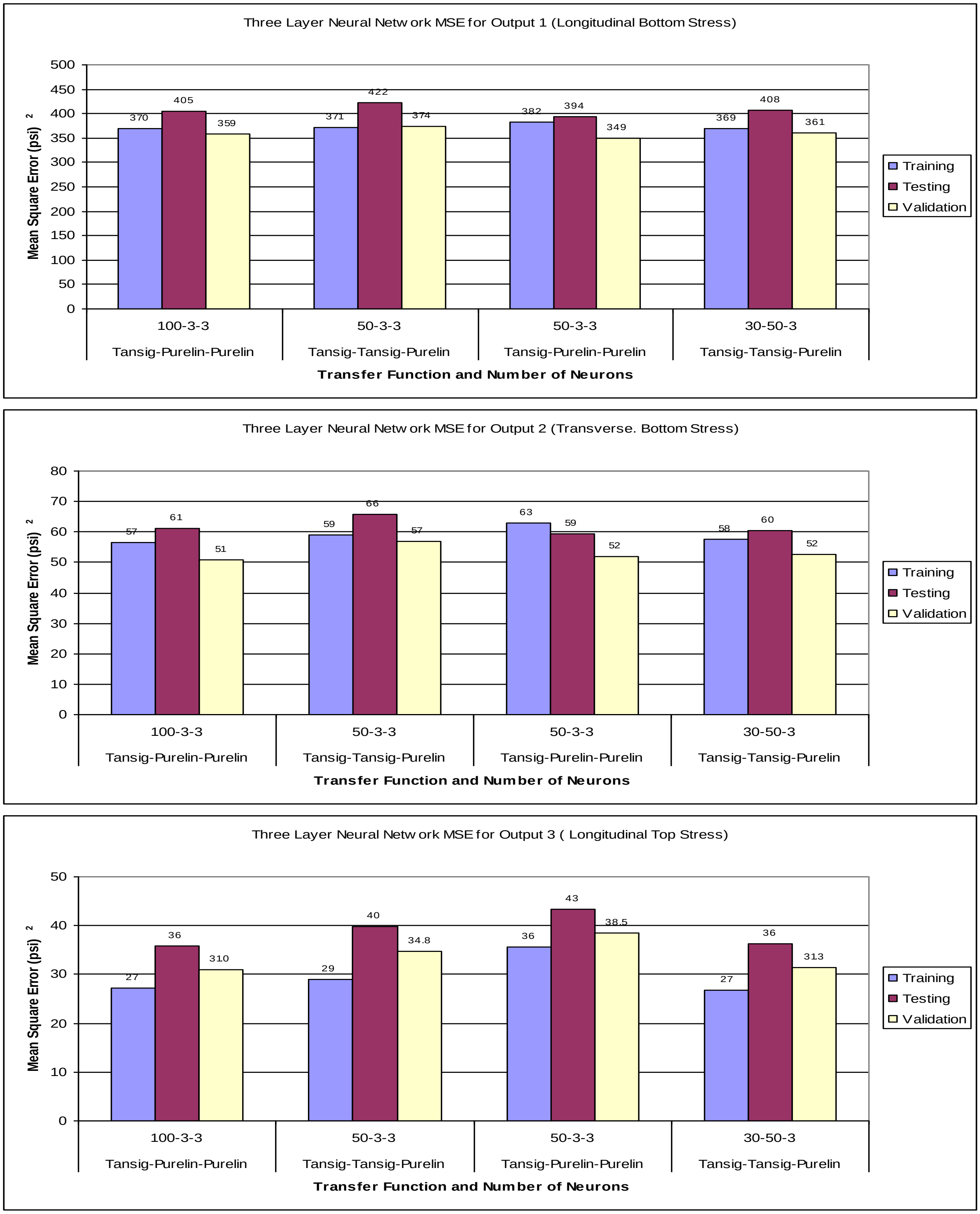


Figure 6. Mean squares for the three layer neural network models

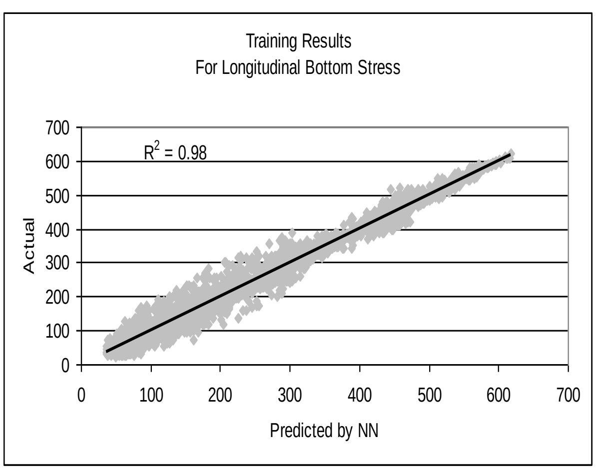
In a two-layer network, one hundred (100) neurons in the first layer with tansig (tangent hyperbola transformation) transfer function and 3 neurons in the second layer with purelin (linear transformation) transfer function works better than all other two-layer models as shown in figure 5. A three layer system, model having 30, 50, 3 neurons in first, second and third layers, respectively, and transfer function tansig in first and second layers and purelin in third layer have a least mean square error as shown in figure 6.

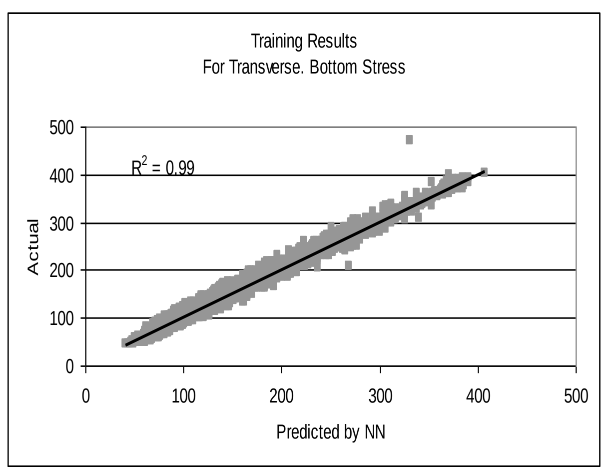
As discuss above, the 100-3 two layer model and the 30-50-3 three-layer model performed better than other models (or architectures). The three-layer models is recommended for this study because it captures the linear and non-linear behavior of the data more effectively than the two layer system, and it has fewer number of neurons. The results for the 30-50-3 three-layer model are presented in the following section.

7. RESULTS

The three-layer neural network model with 30,50 and 3 neurons in first, second and third layers respectively, respectively, was selected as the best configuration. Figures 7, 8 and 9 present the correlations between the predictions by the neural network and the actual values for training, testing and validation data respectively. The neural network shows strong correlation coefficient (R^2) for training, testing and validation data for all three outputs (Longitudinal Bottom, Transverse Bottom and Longitudinal Top Stresses). Note that high R^2 for testing and validation data shows that generalization of the model (network) is possible because this data was not used in the model development.

Two inputs axle type and lateral support were used as discrete variables. Figures 10 and 11 show the sensitivity of trained neural network to these two variables. Axle-type-4-or-more have greater mean square error as compare to the other axle types because this type contains axles from 4 to 8. Reducing the range or using each axle type separately can overcome this problem. However for pavement stresses produced by axles less than 3 are more significant than those by axle-type-4-or-more. Similarly figure 11 shows that the neural network has greater mean square error for AC lateral support and longitudinal bottom stress.





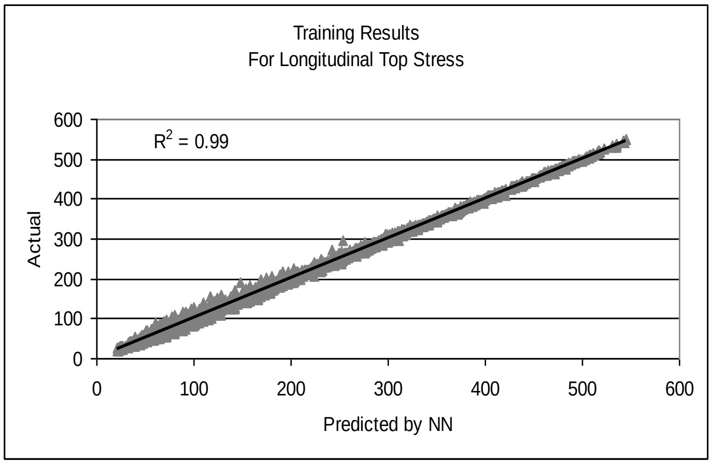
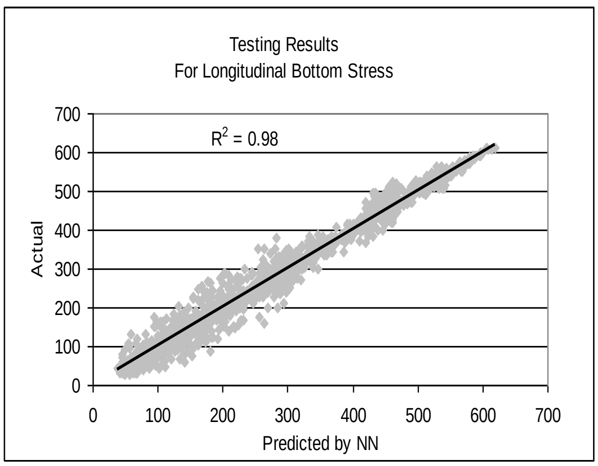
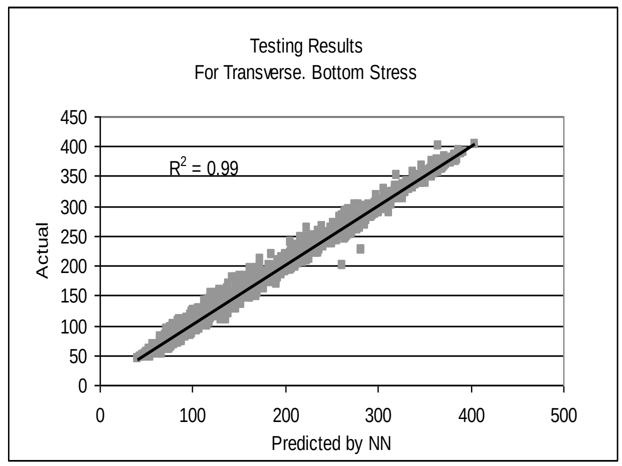


Figure 7. Training data Regression plots for the three outputs.





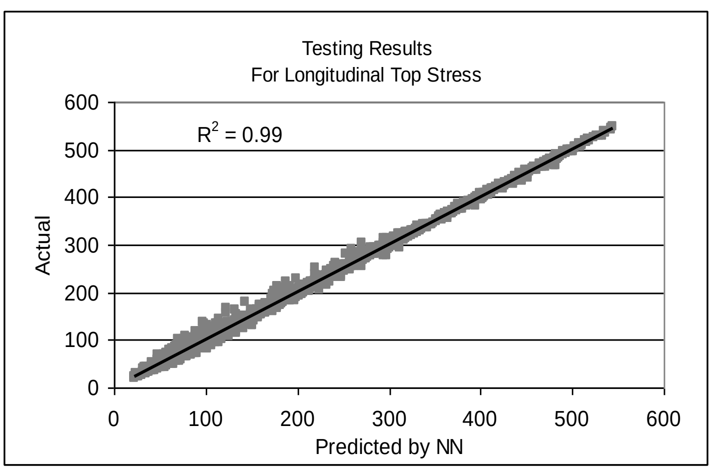


Figure 8. Testing data Regression plots for the three outputs.

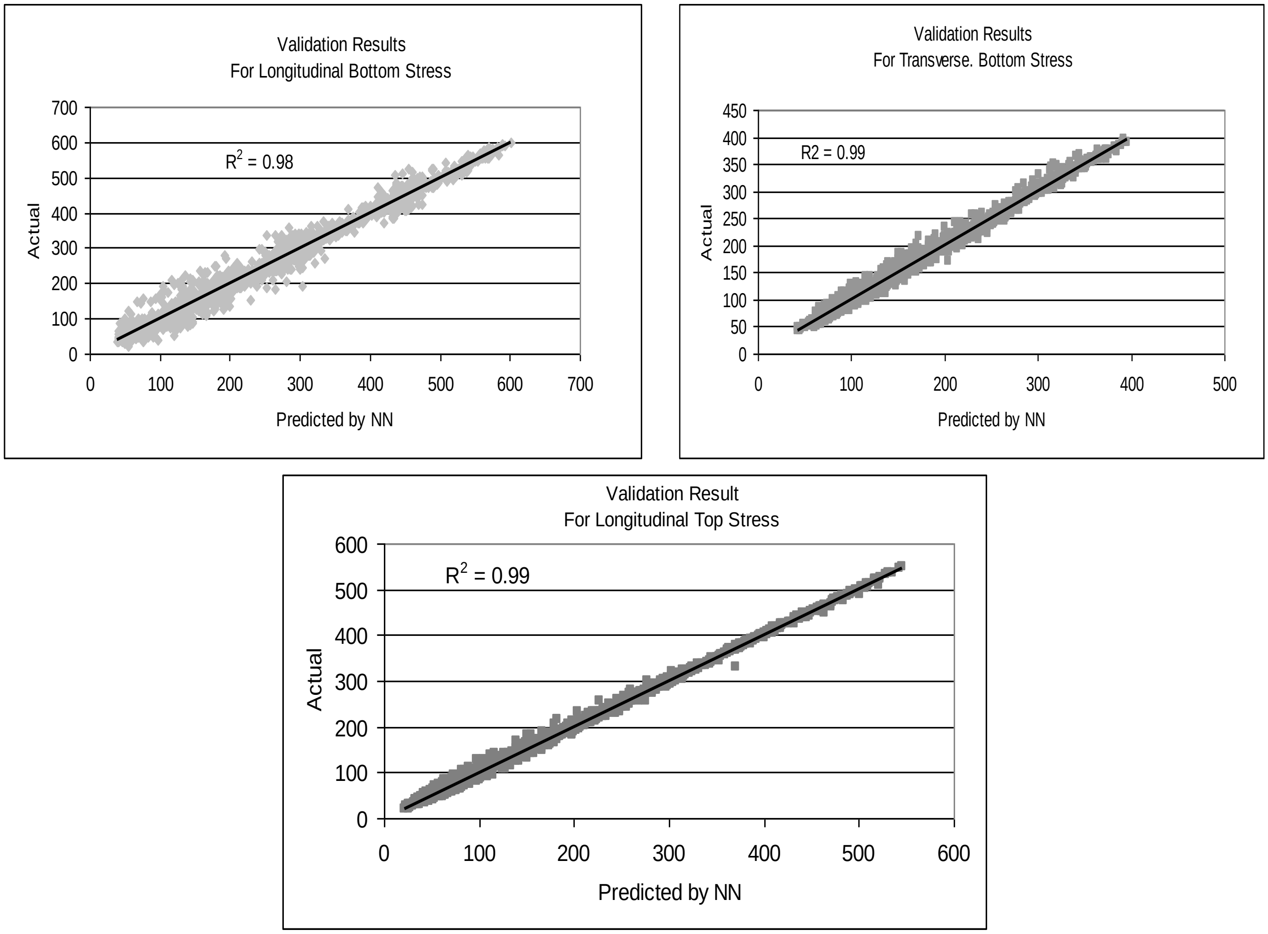


Figure 9. Validation data Regression plots for the three outputs.

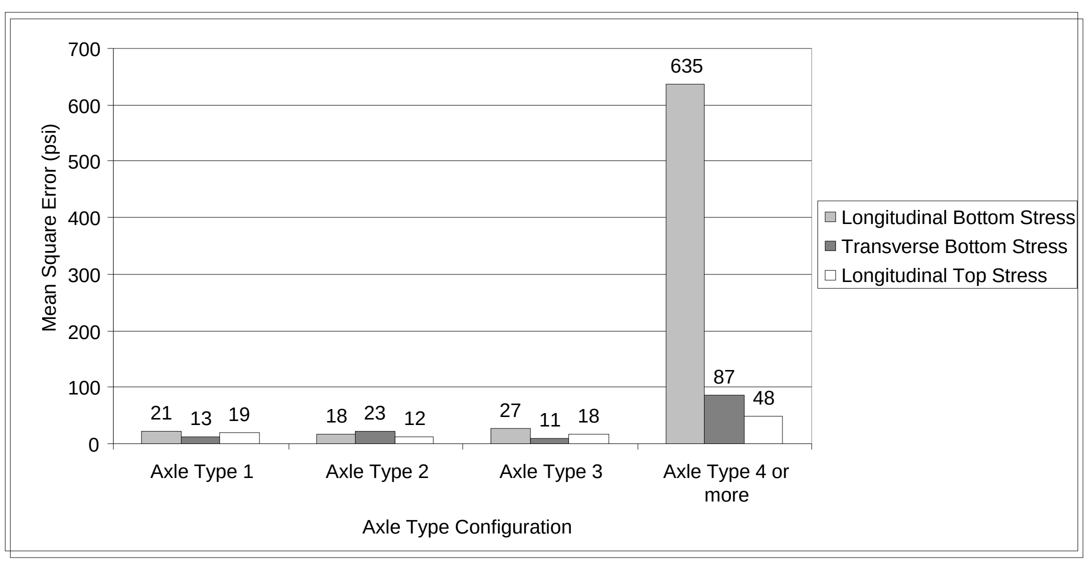


Figure 10. Mean Square Error for different axle type configurations.

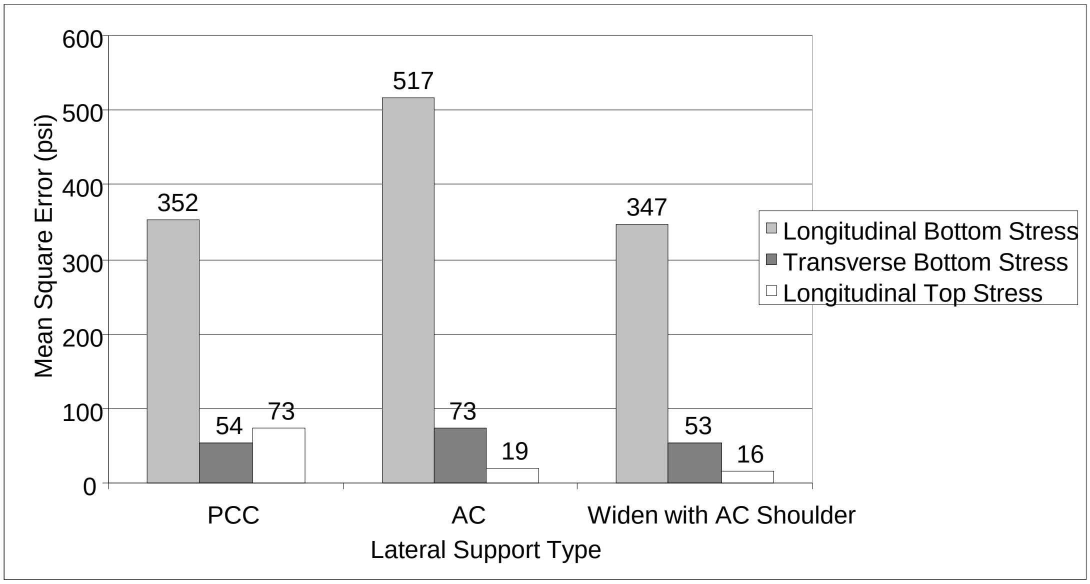


Figure 11. Mean Square Error for different lateral supports.

8. CONCLUSIONS

A neural network-based model is presented that can predict transvers bottom, longitudinal bottom, and longitudinal top stress in jointed concrete pavements. Different architectures were evaluated for best performance. The selected model performed well for predicting all three types of stresses. The coefficient of multiple correlations R^2 and the mean square errors were used as indicators of the effectiveness of the model. The R^2 values for the model predicting the different types of stresses were consistently higher than 0.95. The mean squares errors values were low but not as favorable for all types of stresses under different conditions. Longitudinal bottom stress, in particular, has very high mean square error for the case of 4-or-more-axel. Regardless of the type of lateral support, the mean square error for longitudinal bottom stress is high compared to the other two stress types. The results show that the neural network model is able to generalize and estimate stresses for conditions beyond those used in the development of the model. This is an important feature with significant practical implications: A neural network model can be developed based on limited but representative data that cover practical ranges of traffic, material, and structural conditions. The model can then be used for evaluation of different types of stress, and thus used for design of jointed concrete pavements for combinations of conditions other than those used in the development of the model.

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AUTHOR BIOGRAPHIES

Ghassan Abu-Lebdeh: Associate professor of civil engineering at the American University of Sharjah. Dr. Abu-Lebdeh's research is in control of congested traffic systems and applications for neural and genetic computations in civil engineering. Dr. Abu-Lebdeh holds a Ph.D. from the University of Illinois at Urbana-Champaign. He has over 10- year industry experience in the States of Massachusetts and Illinois. Dr. Abu-Lebdeh is a recipient of the Eisenhower Doctoral Fellowship.

Kamran Ahmed: Assistant professor of civil engineering at the United Arab Emirates University (UAEU). Dr. Ahmad's research is traffic operations and performance and evaluation of pavements. He holds a Ph.D. from Michigan State University. Prior to joining the UAEU, Dr. Ahmed worked at the National University of Science and Technology in Pakistan and with Parsons Engineering in Michigan, USA.