Technical Paper

ISSN 1997-1400 Int. J. Pavement Res. Technol. 2(1):20-25

Artificial Neural Networks and Regression Analysis for Predicting Faulting in Jointed Concrete Pavements Considering Base Condition

Behrooz Saghafi[1+], Abolfazl Hassani[2], Roohollah Noori[3], and Marcelo G. Bustos[4]

Abstract: Pavement management and maintenance is an important aspect of pavement engineering. Maintenance and rehabilitation treatments should be chosen very carefully, considering financial resources and existing distress types. In jointed concrete pavements, transverse joint faulting is a key distress which considerably influences ride quality and road smoothness. There are many factors affecting joint faulting such as heavy traffic, pavement structure, climatic conditions, pavement age, etc. The condition of the base layer is one of those important factors, having a big effect in the performance of jointed concrete pavements. Base layer takes part in both early-age behaviour and long-term performance of jointed concrete pavements. In this research, Artificial Neural Networks (ANNs) and Multivariate Linear Regression (MLR) have been applied in order to predict joint faulting. Pavement age and different base layer parameters where considered in the analysis that used Long Term Pavement Performance (LTPP) project database. Research results show that ANNs approach can predict joint faulting in jointed concrete pavements successfully and more accurately, showing a high coefficient of multiple determination (R^2) values, besides very low amount of error.

***Key words**: Artificial neural networks; Base material; Jointed concrete pavement; Joint faulting; Pavement age.*

Introduction

In the field of pavement engineering, the adequate selection of rehabilitation activities to improve the condition of deteriorated pavement section is a key factor from technical and economical perspectives. Rough roads lead to user discomfort, increased travel times, and higher vehicle operating costs that can lead to millions of dollars in losses to the general economy [1]. So, the engineering judgment and experience on deciding the maintenance and repair actions have significant importance, and pavement maintenance and management system should have the ability to perform evaluation of the current pavement condition and to predict its future performance.

Concrete is widely used as a construction material in pavements by public or private entities which manage highway networks, due to its high durability and capacity to resist large amounts of traffic loads or very severe climates. Transverse joint faulting is one of the main types of distresses in jointed Portland cement pavements (JPCP), that can be defined as the difference in elevation between adjacent slab edges at a transverse joint (Fig. 1). Faulting evolution across time is an important indicator of jointed concrete pavement performance; as faulting increases, pavement roughness and potential of erosion and loss of support beneath the slab are also augmented [2].

1 MSc in Road and Transportation Engineering, Civil Engineering Department, Tarbiat Modares University, Tehran, Iran.
2 Associate Professor, Civil Engineering Department, Tarbiat Modares University, Tehran, Iran.
3 Ph.D Student, Civil Engineering Department, University of Tehran, Tehran, Iran.
4 Assistant Professor, Escuela de Ingenieria de Caminos de Montaña, National University of San Juan, San Juan, Argentina.
+ Corresponding Author: E-mail b.saghafi@2007.ljmu.ac.uk
Note: Submitted July 1, 2008; Revised November 6, 2008; Accepted December 5, 2008.

Scope of Work

Significant joint faulting has a major impact on the life cycle cost of the pavement in terms of early rehabilitation and vehicle operating costs [3]. The crucial importance of being able to predict the future pavement condition can be understood easily when the financial savings are considered.

In this study, artificial neural networks and multivariate linear regression approaches have been applied to consider and to model the effect of base layer conditions and pavement age on joint faulting distress.

Faulting Process in Jointed Concrete Pavements

Joint faulting usually appears as the result of excessive deflection of slab edges and corners caused mainly by heavy wheel loads and/or inadequate load transfer across the joint [3]. Significant differential

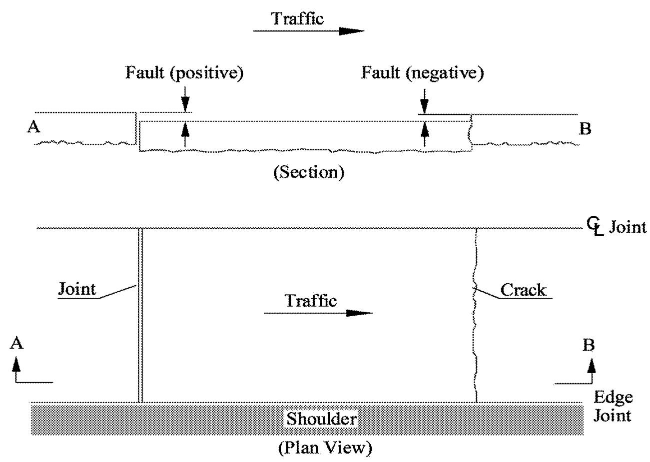
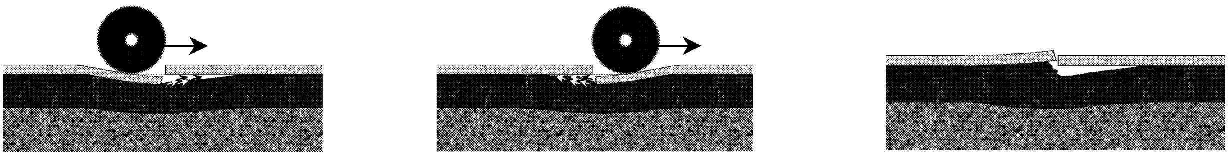
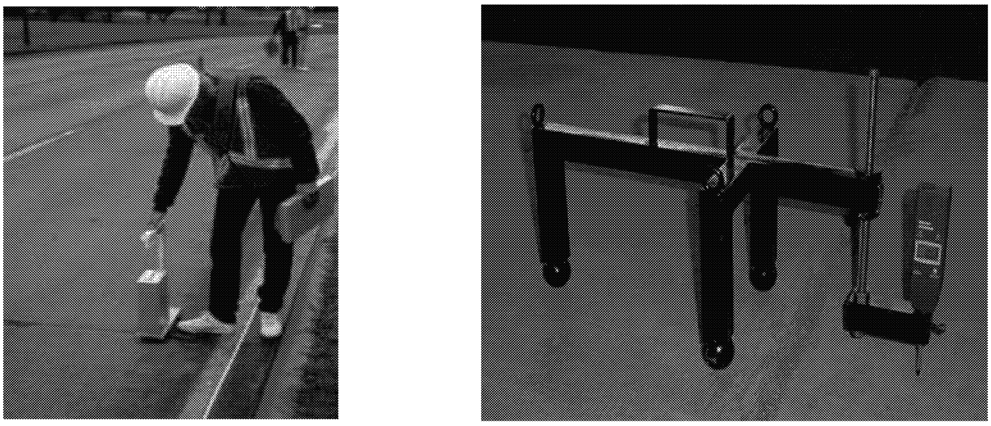


Fig. 1. Faulting of Transverse Joint [2].



(a) (b) (c)

Fig. 2. Scheme of Faulting Progression in JPCPs (a) Wheel on Leave Edge of Slab, (b) Wheel on Approach Edge of Slab, and (c) Resultant Behaviour at the JPCP Joint That Causes Faulting [5].



(a) (b)

Fig. 3. Devices Used to Measure Joint Faulting (a) The Georgia Faultmeter [7] and (b) Digital Faultmeter (Argentina) [8].

deflections impart energy to the underlying pavement material, and when the base is composed of unstabilized or weakly stabilized materials with a high percentage of fines, such deflections cause the movement of the saturated fine material in the presence of free water under the slabs, leading to pumping and erosion [4, 5].

Pumping is caused by the rapid vertical deflection of the leave slab at a joint, which leads to an ejection of fines and water. Eventually, this process results in a void below the leave slab corner and in a deposition under the approach slab corner, which leads to joint faulting (Fig. 2) [2-5].

Previous studies [2-4] show that there are many parameters affecting faulting in jointed concrete pavements such as repeated heavy traffic loads, insufficient load transfer between the adjacent slabs, free water under the slabs, erodible base or underlying fine-grained material (fines), climatic parameters, subgrade condition, section age (after construction or traffic opening), etc. Base type, base erodibility, and base structural aspects are some of the most important parameters influencing the behaviour of jointed concrete pavements [2, 3, 6], although this effect is more pronounced for undoweled JPCPs [6].

Devices for Faulting Measurements

Faulting is measured at each joint at two locations, 0.3*m* from the outside slab edge, called as *edge faulting* and 0.76*m* from the outside slab edge, called as *wheel-path faulting* [2]. Such measurements can be done using faultmeter devices. Georgia Faultmeter, an electronic digital device used for gathering faulting information, was designed, developed, and built by the Georgia Department of Transportation, as shown in Fig. 3(a). It reads out directly in milimeters and shows whether the reading is positive or negative [7]. Another type of faultmeter, used in Argentina for specific studies [8], is shown in Fig. 3(b). It includes an electronic device that measures the difference in height between the plane defined by the footprints on the approach slab, and the point of the device, located on the leave slab.

Base Layer in Jointed Concrete Pavements

Although current empirical design procedures such as AASHTO 1993 (American Association of State Highway and Transportation Officials) indicate that the base layer provides only minimum structural capacity to the pavement, this may be misleading. Base condition plays a very important role since it influences both early-age behaviour and long-term performance of JPCP. The potential for base erosion has a significant impact on concrete slab support and on the initiation and propagation of pavement distress.

Granular bases with a high amount of crushed materials, low fine content, and low plasticity, considerably reduce pumping of subgrade and improve resistance to the effects of moisture. However, stability of these untreated permeable base layers is a major concern because settlement can lead to serious problems and needs to be addressed adequately [9].

Treated bases, on the other hand, are effective in reducing pumping and controlling joint faulting. Pavements constructed on cement-stabilized base materials, such as lean concrete bases, typically experience less faulting and their corner deflections generally are reduced [4]. Also, high-quality crushed aggregates are needed to ensure long-term durability [9] in cement-stabilized layers.

Hot-mix asphalt base materials can also be effective in minimizing moisture problems in jointed concrete pavements.

Generally, high asphalt content ensures adequate film thickness around the aggregates, thereby increasing resistance to moisture [9].

Research Analysis Approaches

Two approaches were examined in this research: Artificial Neural Networks (ANNs) and Multivariate Linear Regression (MLR) method. The performance of two highly-used methods, ANNs and MLR, in the problem of predicting joint faulting in jointed concrete pavements is compared.

Artificial Neural Networks

ANNs approach is a valuable computational tool that is increasingly being used to solve resource-intensive complex problems as an alternative to using more traditional techniques. ANNs have been used in pavement deterioration [10, 11], pavement performance prediction [12-16], flexible pavement cracking prediction [17], and condition rating of jointed concrete pavements [18].

ANNs act very similar to the human brain, by receiving input (data values) and processing them through a series of nodes that organize themselves so as to best predict a certain output. Receiving stimuli (inputs) numerous times and arriving at the best association between the stimuli and an output is termed *learning* [19, 20].

Backpropagation ANNs are very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of patterns to be learned. Actually, backpropagation algorithm is essentially a gradient descent technique that minimizes the network error function [19, 21]. Involving two steps, in the first one, the effect of the input is passed forward through the network and in the second step, an error between the measured values (or targets of the model) and the predicted outputs is estimated at the output layer. Then the calculated error is backpropagated toward the input layer through each hidden node to adjust the connection weights. After many examples (training patterns) have been propagated through the network for many times, the mapping function is learned with some specified error tolerance. This is called supervised learning because the network has to be shown the correct answer for it to learn [19].

Multivariate Linear Regression Method

MLR method is a primal, useful technique which has been applied in all fields of engineering knowledge, in a large variety of model making problems. Generally, Eq. (1) is the matrix form of a MLR model.

$$Y = X\beta + e \tag{1}$$

where Y is the response matrix, X is the matrix of explanatory variables, β is the regression coefficient matrix and e is the fitting error matrix. If Eq. (1) is solved for β, Eq. (2) will be developed.

$$\beta = (X'X)^{-1}(X'Y) \tag{2}$$

where X' is the transpose form of matrix X.

In this research, a model has been developed to predict faulting distress considering base condition and pavement age, using the MLR technique. Stepwise algorithm has been used for regression calculations, where the variables are evaluated in the model step by step according to their importance in improving model performance.

Criteria for Assessing Model Performance

One of the criteria used for assessing the performance on both MLR model and ANNs is coefficient of multiple determinations (R^2). Legates and McCabe indicated that being R^2 affected by 'far' data, other criteria are necessary for assessing model performance accurately [22]. Therefore, two others, root mean square error (*RMSE*) and mean absolute error (*MAE*) have been used to assess model performance. The equations of these criteria are as follow:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_o - x_p)^2}{\sum_{i=1}^{n}(x_o - x'_o)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_o - x_p)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_o - x_p\right| \tag{5}$$

where if X is the matrix of explanatory variables (matrix of faulting readings, in this research), x_o is the actual value of X_i with $i = 1, 2, \cdots, n$ observations, x'_o is the average of X_i, x_p is the predicted values of X_i and n is the total number of observations.

LTPP Data Used for This Research

Long Term Pavement Performance (LTPP) program started in 1978 with a comprehensive study of in-service pavements and long-term field experiments, monitoring more than 2,400 flexible and rigid pavement test sections through United States and Canada. LTPP database is mainly divided into two major categories namely General Pavement Studies (GPS) and Specific Pavement Studies (SPS) [23].

Transverse joint faulting is being monitored regularly at the jointed concrete pavement test sections under the LTPP program, using the Georgia Faultmeter. Average transverse joint faulting is a representative faulting value of both edge and wheel-path faulting for each site measurement. Joint faulting and base layer data used in this research are gathered out of SPS-2 and GPS-3 databases, including average transverse joint faulting (*mm*), age of the

Table 1. Inputs and Output Description.

Node	Node Description	Role
1	Age (months)	Input
2	Base Material	Input
3	Base Type	Input
4	Thickness (*cm*)	Input
5	Erodibility Class	Input
6	Percent Passing No. 4 Sieve	Input
7	Percent Passing No. 200 Sieve	Input
8	Resilient Modulus (*MPa*)	Input
9	Mean Transverse Joint Faulting (*mm*)	Output

Table 2. The Results of Inputting Variables in the MLR Model.

Parameter	Description	Variable Coefficient in MLR Model	Significance Level
Constant	-----	-0.88385	<0.01
Input 1 (x_1)	Age (months)	0.008944	<0.01
Input 2 (x_2)	Base Material	0.046697	0.01
Input 5 (x_5)	Erodibility Class	0.22448	<0.01
Input 6 (x_6)	Percent Passing No. 4 Sieve	-0.01659	<0.01
Input 7 (x_7)	Percent Passing No. 200 Sieve	0.034415	0.04

pavement (months), base type and material description, base thickness, erodibility, resilient modulus (*MPa*), etc.

Performance of ANNs for Predicting Faulting in JPCP

In this study, a feed-forward, multi-layer, backpropagation network was developed to predict joint faulting in jointed concrete pavements, using 405 random observation data, gathered out of LTPP SPS-2 and GPS-3 programs. Eight variables were selected as inputs, and the output was the mean transverse joint faulting. Table 1 indicates the variables used as inputs and output.

The available data were split into three parts:

(1) a training set, used to determine the network weights;
(2) a validation set, used to estimate the network performance and decide when we stop training;
(3) a prediction (or test) set, used to verify the effectiveness of the stopping criterion and to estimate the expected performance in the future.

Materials used in the base layer of the inspected sections have been divided into 14 different types by LTPP. As well, LTPP has categorized base types into two main categories: granular bases (GB), and treated bases (TB).

405 data were divided into three parts: training, testing, and validation. In the training phase, 250 records (approximately 60% of the whole data) were used by MATLAB 7.0 software to develop the networks. In the testing phase, 80 (approximately 20% of the whole data) unique faulting records were used as input for testing the trained neural network. Remaining 75 records (approximately 20% of the whole data) helped for validating the network. Validating is a process applied in order to overcome network over-fitting, using Stop Training Approach.

Several ANNs architectures were studied to obtain the best results, thus the network was trained using both 3- and 4-layered ones, each layer including different numbers of neurons. Finally, the best results were obtained by an 8-8-8-1 network structure, i.e. 8 neurons in the input layer, 8 neurons in the first hidden layer, 8 neurons in the second hidden layer, and a neuron in the output layer.

The developed ANNs model was able to successfully predict the measured joint faulting with coefficient of R^2 values of 0.96 for the training data set and 0.94 for the testing data set. *MAE* of both training and testing sets was applied to inspect the amount of errors between measured and predicted faulting values. Calculations resulted in *MAE* = 0.09 for training and *MAE* = 0.23 for testing phases. These little levels of errors indicate that this network architecture has been correctly designed. Figs. 4 and 5 depict the actual versus predicted faulting values for both training and testing phases.

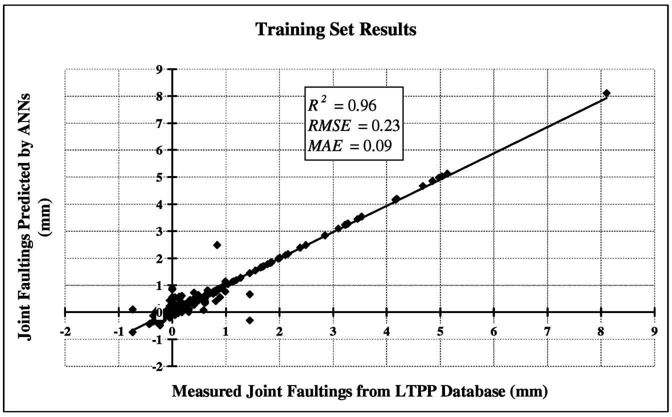


Fig. 4. Performance of the 8-8-8-1 Network for Predicting Joint Faulting in JPCPs – Training Set Results.

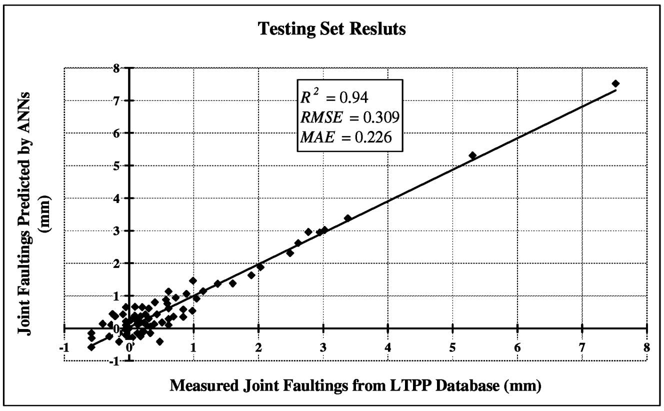


Fig. 5. Performance of the 8-8-8-1 Network for Predicting Joint Faulting in JPCPs – Testing Set Results.

To check that the dependent variable has a normal distribution, the Kolmogorov-Smirnov method was used to confirm such hypothesis [24]. Therefore, a simplified model was developed to predict joint faulting using MLR and the stepwise algorithm of MLR method, considering significance level of 5%. This could be done by considering five variables (input parameters) out of eight as using just five variables in the model could achieve the desired level of significance. Table 2 shows the selected variables and their corresponding significance level when co-operating in developing a faulting prediction model.

$$\begin{aligned} Faulting = & -0.88385 + 0.008944x_1 + 0.046697x_2 + 0.22448x_5 \\ & -0.01659x_6 + 0.034415x_7 \end{aligned} \tag{6}$$

R^2 = 0.54; *RMSE* = 0.79; *MAE* = 0.55.

According to Table 2, the model presented in Eq. (6) shows clearly the influence of parameters like pavement age and base layer materials and characteristics on faulting. To compare the performance of MLR model and the results taken from the selected ANNs, performance details of the MLR model have been calculated for the data used for training and testing ANNs and the results have been demonstrated in Figs. 6 and 7.

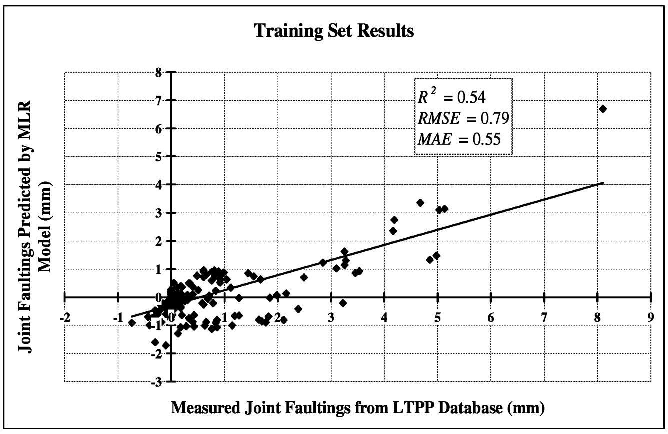


Fig. 6. Performance of the MLR Faulting Prediction Model – Training Set Results.

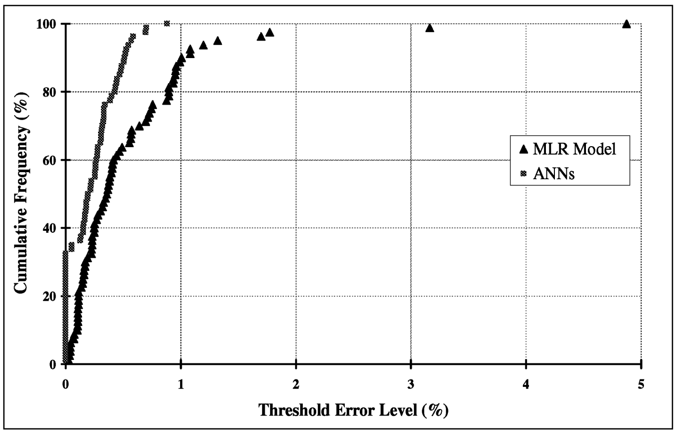


Fig. 8. Performance of the MLR Faulting Prediction Model – Training Set Results.

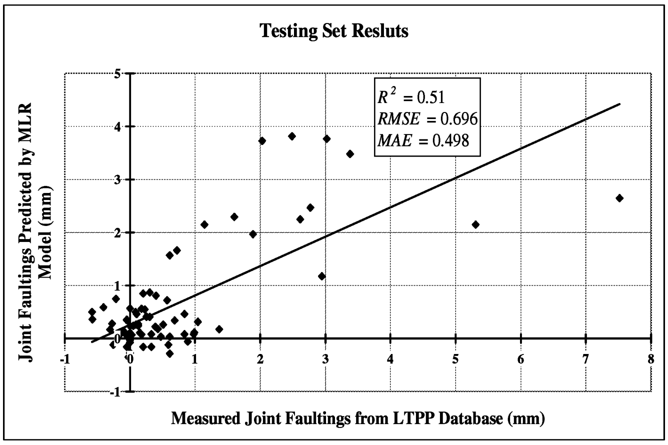


Fig. 7. Performance of the MLR Faulting Prediction Model – Testing Set Results.

Discussion

To compare the performance of these two approaches, the criteria calculated for each approach have been presented in previous sections. Having noted to the mathematical definitions of the criteria, MLR modelling results and ANNs performance already shown, it is clearly obvious that the final ANN has been able to predict faulting much more accurately since it has acquired higher R^2 values for training and testing faulting data with very low amounts of errors.

Further, for demonstrating the performance of the approaches to compare them more meaningfully, a scattering diagram has been developed based on cumulative absolute mean errors, showing the cumulative frequencies of data (%) against threshold error levels (%) for both MLR model and ANNs in testing stage. According to Fig. 8, cumulative absolute error for whole testing data is less than 0.9% when the faulting values have been predicted using ANNs but this amount is less than 4.9% for faulting values predicted by the developed MLR model. Also, trained ANNs could predict 75% of faulting values with errors less than 0.3% while MLR model did so with about 0.7% of errors. The overall diagram shows clearly that the performance of the ANNs is remarkably better than what MLR model did.

Therefore, it is concluded that the trained ANNs can predict faulting values with less errors in comparison with the MLR model. Nevertheless, the MLR model has the advantage of being easier to be understood because the relative incidence of each variable is directly addressed by the model.

Conclusions

This paper demonstrates a successful use of the artificial neural networks (ANNs) to model the complex relationship between pavement age and parameters related to base layer conditions and joint faulting in jointed concrete pavements. The four-layer back-propagation neural network proposed in this paper showed strong prediction capability as it could predict the measured joint faulting values with the coefficient of multiple determination (R^2) values of 0.96 for training data set and 0.94 for testing data set, with mean absolute error (MAE) of 0.09 for training data set and 0.23 for testing data set. High amount of R^2 beside little error amounts imply a valuable success in predicting joint faulting considering base layer conditions and pavement age, using the 8-8-8-1 network. ANNs also show a higher capacity to predict joint faulting more accurately, compared with MLR models developed with the same data.

References

1. Titus-Glover, L., (2001). Appendix PP: Smoothness Prediction for Rigid Pavements, Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, *Final Report, NCHRP 1-37A Project*, Transportation Research Board, Washington, D.C., USA.
2. Selezneva, O., Jiang, J., and Tayabji, S.D., (2000). Preliminary Evaluation and Analysis of LTPP Faulting Data, *Final Report*, *Publication No. FHWA-RD-00-076*, Federal Highway Administration, U.S. Department of Transportation, VA, USA.
3. Khazanovich, L., (2003). Appendix JJ: Transverse Joint Faulting Model, Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, *Final Report, NCHRP 1-37A Project*, Transportation Research Board, Washington, D.C., USA.
4. Ruiz, J.M., Rasmussen, R.O., Chang, G.K., Dick, J.C., and Nelson. P.K., (2005). Computer-Based Guidelines for Concrete Pavements (Volume II: Design and Construction Guidelines

and HIPERPAVE II User's Manual), *Publication No. FHWA-HRT-04-122*, Federal Highway Administration, U.S. Department of Transportation, VA, USA.

5. Titus-Glover, L., Owusu-Antwi, E., and Darter, M.I., (1999). Design and Construction of PCC Pavements (Volume III: Improved PCC Performance), *Report No. FHWA-RD-98-113*, Federal Highway Administration, U.S. Department of Transportation, Washington, D.C., USA.
6. ERES Consultants, (2003). Effect of Base Type on the Performance of Jointed Concrete Pavements, *Subtask to Caltrans Task Order 11*, Prepared by ERES Consultants, IL, USA.
7. Miller, J.S. and Bellinger, W.Y., (2003). Appendix B: Manual for Faultmeter Measurements, Distress Identification Manual for the Long Term Pavement Performance Program, *Publication No. FHWA-RD-03-031*, Federal Highway Administration, U.S. Department of Transportation, VA, USA.
8. Bustos, M., Marcet, J., Cordo, O., Girardi, P., Pereyra, M., and Altamira, A., (2006). Concrete Pavement Performance in Midwestern Argentina Compared with Long-Term Pavement Performance Data: HD4-4 Distress Models, *"Rigid and Flexible Pavement Design 2006", Transportation Research Record*, No. 1947, pp. 110-120.
9. NCHRP 1-37A, (2004). Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, *Final Report, NCHRP 1-37A Project*, Transportation Research Board, Washington, D.C., USA.
10. Alsugair, A.M. and Al-Qudrah, A.A., (1998). Artificial Neural Network Approach for Pavement Maintenance, *Journal of Computing in Civil Engineering*, ASCE, 12(4), pp. 249-255.
11. Attoh-Okine, N.O., (2001). Grouping Pavement Condition Variables for Performance Modeling Using Self-Organizing Maps, *Journal of Computer-Aided Civil and Infrastructure Engineering*, 16(2), pp. 112-125.
12. Ceylan, H., Guclu, A., Tutumluer, E., Thompson, M.R., and Gomez-Ramirez, F., (2004). Neural Network-Based Structural Models for Rapid Analysis of Flexible Pavements with Unbound Aggregate Layers, *Proceedings of 6th International Symposium on Pavements Unbound (UNBAR 6)*, Nottingham, England, pp. 139-147.
13. Attoh-Okine, N.O., (1994). Predicting Roughness Progression in Flexible Pavements Using Artificial Neural Networks, *Proceedings of 3rd International Conference on Managing Pavements*, Texas, USA, pp. 55-62.
14. Choi, J., Adams, T.M., and Bahia, H.U., (2004). Pavement Roughness Modeling Using Backpropagation Neural Networks, *Journal of Computer-Aided Civil and Infrastructure Engineering*, 19(4), pp. 295-303.
15. Eldin, N.N. and Senouci, A.B., (1995). A Pavement Condition Rating Model Using Backpropagation Neural Network, *Journal of Microcomputer in Civil Engineering*, 10(6), pp. 433-441.
16. Robert, C.A. and Attoh-Okine, N.O., (1998). A Comparative Analysis of Two Artificial Neural Networks Using Pavement Performance Prediction, *Journal of Computer-Aided Civil and Infrastructure Engineering*, 13(5), pp. 339-348.
17. Owusu-Ababia, S., (1998). Effect of Neural Network Topology on Flexible Pavement Cracking Prediction, *Journal of Computer-Aided and Infrastructure Engineering*, 13(5), pp. 349-355.
18. Attoh-Okine, N.O., (2002). Combining Use of Rough Set and Artificial Neural Networks in Doweled-Pavement-Performance Modeling – A Hybrid Approach, *Journal of Transportation Engineering*, ASCE, 128(3), pp. 270-275.
19. Haykin, S., (1999). *Neural Networks: A Comprehensive Foundation*, 2nd Edition, Prentice Hall Publication, Englewood Cliff, NJ, USA.
20. MATLAB, version 7.0 Software Help.
21. ASCE Task Committee, (2000). Artificial Neural Network in Hydrology. *Journal of Hydrologic Engineering*, ASCE. 5(2), pp. 124-144.
22. Legates, D.R. and McCabe, G.J., (1999). Evaluating the Use of "Goodness-of-Fit" Measures in Hydrologic and Hydro Climatic Model Validation, *Water Resource Research*, 35(1), pp. 233-241.
23. LTPP User Guide, (2004). Long Term Pavement Performance Information Management System, *Pavement Performance Database User Guide*, Federal Highway Administration, U.S. Department of Transportation, USA.
24. Manly, B.F.J., (1986). *Multivariate Statistical Methods: A Primer*, Chapman & Hall, 2nd Edition, London, England.