Predicting Roughness Progression in Flexible Pavements Using Artificial Neural Networks

Nii O. Attoh-Okine, *Florida International University*

To develop a balanced expenditure program for a highway network, the rate of deterioration of the pavement and the nature of changes in the condition need to be predicted so that timing, type, and cost of maintenance can be estimated. A pavement deterioration model, or pavement performance, is therefore a key component of the analysis supporting pavement management decision making. Models for predicting roughness progression have been developed on the basis of traffic and time-related models, interactive time, traffic, or distress models. These models differ in form, in level of initial roughness, and in the influence of roughness on the subsequent progression rate. A characteristic feature of the models is that they are formulated and estimated statistically from field data. To date, modeling pavement performance has been extremely complicated; no pavement management system (PMS) can consider more than a few of the parameters involved, and then only in highly simplified manner. The capabilities of artificial neural networks (ANNs) are evaluated in predicting roughness progression in flexible pavement from structural deformation, which is the function of modified structural number, incremental traffic loadings, extent of cracking and thickness of cracked layer, incremental variation of rut depth; surface defects, which are the function of changes in cracking, patching and potholing; and environmental and non-traffic-related mechanisms, which are the function of pavement environment, time, and roughness. ANNs have attracted considerable interest in recent years because of growing recognition of the potential of these networks to perform cognitive tasks. The tasks include prediction, knowledge processing, and pattern recognition. ANNs offer a number of advantages over more traditional statistical prediction methods: they are capable of generalization, and because of their massive parallelism and strong interconnectivity, they are capable of offering real-time solutions to complex problems. The back-propagation algorithm, which uses supervised learning, is used to train the networks.

Road roughness is defined as the deviation from a true planar surface with a characteristic dimension that affects vehicle dynamics, ride quality, dynamic loads, and drainage. Roughness, which is the irregularity of the road surface familiar to all road users, and the perceptions of the riding quality of a road have long been considered criteria for the acceptability of the service provided by the road. Roughness affects the dynamics of moving vehicles, increasing the wear on vehicle parts. It also increases the dynamic loadings imposed by vehicles on the surface, accelerating the deterioration of pavement structure as discussed by Paterson (*1*).

Predicting the progression of roughness during pavement design life is very important for pavement management decision making, pavement design and evaluation, and road pricing. Many different models for characterizing roughness progression in flexible pavements systems are shown in Table 1. The merits and drawbacks of traffic, time-related, and interactive time-traffic models have been discussed by Paterson (*2*). New transferable causal

TABLE 1 Selected Previous Model Forms for Characterizing Roughness Progression

MODEL FORMS	SOURCE AND COMMENT
*Traffic Models	
1. $g_t=(p_0-p_t)/(p_0-p_r)=(N_t/\rho)^{\beta}$	AASHTO from 1959-60 Road Test, Illinois
2. $R_t=R_0+s(S)N_t$	RTIM2 Model from 1971-75 Kenya-TRRL Road Cost Study
3. $g_t=\exp[-(\rho/N_t)^{\beta}]$	USA (Lytton et al. 1982); S-shaped curve of slope ρ and curvature β
*Time Related Models	
4. $\Delta R_t=aR_t\Delta t-b$	Arizona, USA (Way and Eisenberg 1980).
5. $R_t=R_0+at^b$	Australia (Potter 1982).
6. $\Delta R_t/R\cong7\%$	Canada (Cheetham and Christison 1981).
20 -30% per year	Spain, Belgium (Lucas and Viano 1979)
*Interactive time, traffic or distress	
7. $R_t=a+bt+cf(S,\log N_t)$	Brazil (Queiroz 1981).
8. $\Delta R_t/R_t=\max(aCX^b,c)\Delta t$	Great Britain (Jordan et al. 1987).
9. $t=f[p_0,\ RD, RD^{2.5}, (C+P)^{0.5}]$	(Uzan and Lytton 1982).
Generalized Models	
10. $RI_t=e^{mt}[RI_0+a(1+SNC-F\ HS\ CRX)^{-5}NE_t]$ $+cRDS_t+dCRX_t+ePAT_t$	(Paterson and Attoh-Okine 1993(3)).
11. $RI_t=e^{mt}+[RI_0+a(1+SNC)^{-5}NE_t]$ $+d\ CRX_t+ePAT_t$	(Paterson and Attoh-Okine 1993(3)).
12. $RI_{noc}=e^{mt}[RI_0+a(1+SNC)^{-5}NE_t]$	(Paterson and Attoh-Okine 1993(3)).
13. $RI_t=e^{mt}[RI_0+a(1+SNC-F_iHS\ CRX)^{-5}NE_t]$	(Paterson and Attoh-Okine 1993(3)).
14. $RI_t=e^{mt}[RI_0+a(1+SNC)^{-5}NE_t]$	(Paterson and Attoh-Okine 1993(3)).
15. $RI_t=e^{mt}[RI_0+a(1+SNC-F\ HS\ CRX)^{g}NE_t]$	(Paterson and Attoh-Okine 1993(3)).
16. $RI_t=e^{mt}[RI_0+a(1+SNC)^{g}NE_t]$	(Paterson and Attoh-Okine 1993(3)).
17. $RI_t=e^{mt}[RI_0+a(1+SNC)^{g}NE^{h}{}_t]$	(Paterson and Attoh-Okine 1993(3)).

* Adapted from (2)

Note: g = damage function; p = serviceability index; N_t = cumulative number of ESAL's; R = roughness; S = pavement strength parameter; t = age of pavement since rehabilitation; CRX = area of cracking; RD = rut depth; C + P = area of cracking plus patching; β, ρ, are functions, and a, b, and h are constants estimated empirically through research; RI_t = roughness at pavement age t; m = environmental coefficients; NE_t = cumulative equivalent standard axle loads; SNCK = (1 + SNC − F HS CRX_t); SNC = structural number modified for subgrade strength; F − coefficient; HS = thickness of bound layers; CRX_t = area of indexed cracking at time t; RDS_t = standard deviation of rut depth; PHV_t = volume of potholing; PAT_t = area of patching.

models (*2*) and generalized models described by Paterson and Attoh-Okine (*3*) have been developed (Table 1). To date, the models developed for predicting roughness have concentrated primarily on the expected or average future performance of the pavement. The outcome is based on statistical prediction methods.

Artificial neural networks (ANNs) have been shown to offer a number of advantages over traditional statistical methods. They are capable of making generalizations and of offering real-time solutions to complex prediction problems because of their massive parallelism and strong interconnection. Because ANNs learn from pavement historical data, no human expert, specific knowledge, or developed models are needed.

The aim of this paper is to evaluate the capabilities of ANNs in predicting roughness progression in flexible pavement from structural deformation (modified structural number, incremental traffic loadings, extent of cracking and thickness of cracked layer, and incremental variation of rut depth), surface defects (changes in cracking, patching, and potholing), and environmental and non-traffic-related mechanisms (pavement environment and time). ANNs are particularly suited to such a task because they are "taught," that is, exposed to data, allowed to "learn," and "told" what are the appropriate responses to different inputs.

Artificial Neural Network Approach

ANNs, or simply neural networks, are computing systems made up of a number of simple and highly interconnected elements that process information by its dynamic-state response to external inputs, as described by Kamarthi et al. (*4*). ANNs have been studied for many years, but there has been a recent resurgence of interest in this rapidly growing area in artificial intelligence (AI). ANNs are a form of AI designed from a blueprint of the brain that simulates the brain's capability to think and learn through perception, reasoning, and interpretation. Important characteristics of a neural network are its ability to "learn" and "adapt" and its flexibility and parallelism.

Unlike expert systems, ANNs are capable of learning the interrelationship between the parameters of a problem by looking at some typical examples. ANNs are very flexible and can be thought of as black boxes that could be adapted for any problem. With today's advances in computer technology, the parallel structure of ANNs helps in the implementation and real-time applications. ANNs can operate simultaneously on both quantitative and qualitative data, and they naturally process many inputs and have many outputs that make them readily applicable to multivariate systems.

The basic unit of an ANN is a processing element (PE). It combines (typically sums) the inputs and produces an output in accordance with a transfer function (typically a threshold function). The output of one processing element is connected to the input paths of other processing elements through connecting weights. The PEs by themselves are not powerful in terms of computation or representation, but their interconnection allows analysts to encode relations between variables, giving different powerful processing capabilities. Figure 1 displays the anatomy of a single PE. The inputs' signals come from either the environment or outputs of other PEs and form an input vector $\mathbf{A} = (a_1, \ldots a_i \ldots a_n)$, where a_i is the activity level of the ith PE or input. Associated with each connected pair of PEs is an adjustable value called weight (also referred to as a connection strength). The collection of weight forms a vector $\mathbf{W}_j = (w_{1j}, \ldots w_{ij} \ldots w_{nj})$, where the weight w_{ij} represents the connection strength from PE a_i to the PE b_j. And finally the bias θ_j is used to compute the output value b:

$$b_j = f(AW_j - W_{0j}\theta_j) \tag{1}$$

$$b_j = f\left(\sum_{i=1}^{n} a_i W_i - W_{0j}\theta_j\right) \tag{1a}$$

Development of ANN Model

Data Generation

Roughness data were generated using the RODEMAN, a menu-driven PC version of the Road Deterioration and Maintenance Submodel of HDM-III. The approach utilizes a full empirical simulation model to generate roughness data. Table 2 is the example subset of data generated, and Table 3 shows the combination. There were 1,274 discrete data items.

Data Preparation

The phases of data preparation for the modeling were broadly classified into three distinct areas: data specification, data inspection, and data preprocessing. The data specification was determined during the generation of variables from the simulation. After the data were identified, box-and-whiskers plots were used to determine if there were outliers. An outlier is an extreme data point that may have undue influence on a model. Outliers are often (but not always) caused by erroneous data cases.

Box-and-whiskers plots are based on a "five-number summary," which consists of the median, the two quar-

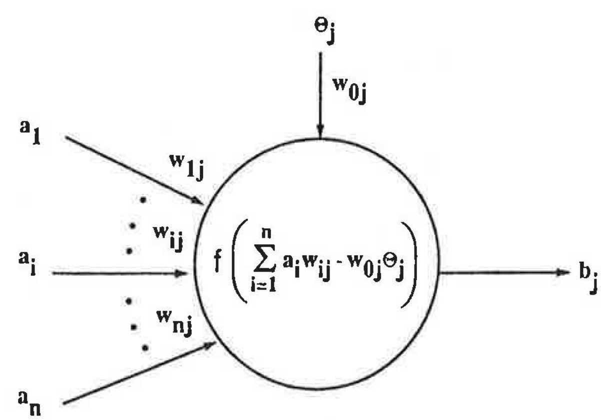

FIGURE 1 Artificial neural system.

TABLE 2 Example Subset of Data Generated by HDM-III Model

SNC	AADT veh/d	ESALY Million	AGE yr	CRA %	CRW %	CRX %	RAV %	PHA- %	RDM mm	RDS mm	RI IRI=	PAT %
3	1000	0.10	0	0	0	0	0	0	0	0	2.0	0.00
			1	0	0	0	0	0	3.0	1.3	2.21	0.00
			2	0	0	0	0	0	3.4	1.4	2.28	0.00
			3	0	0	0	0	0	3.8	1.5	2.36	0.00
			4	0	0	0	0	0	4.1	1.5	2.43	0.00
			5	0	0	0	0	0	4.3	1.6	2.51	0.00
			6	2	0	1	0	0	4.5	1.6	2.59	0.00
			7	6	0	4	0	0	4.7	1.7	2.69	0.00
			8	12	3	8	0	0	4.9	1.7	2.80	0.00
			9	20	9	16	0	0	5.1	1.7	2.94	0.00
			10	31	19	26	0	0	5.2	1.7	3.09	0.00
			11	44	31	39	0	0	5.4	1.8	3.27	0.00
			12	59	45	54	0	0.03	5.6	1.8	3.47	0.03
			13	72	61	68	0	0.04	5.8	1.9	3.68	0.07
			14	82	74	80	0	0.06	6.0	1.9	3.87	0.13
			15	90	85	89	0	0.07	6.2	2.0	4.06	0.20
			16	95	93	95	0	0.08	6.4	2.0	4.23	0.28

1. Potholing area data shown is prior to patching, and is reduced to zero annually by the patching.
2. 1 m/km IRI = 63.36 inch/mi IRI.

Note: SNC = Modified Structural Number

TABLE 3 Combinations and Ranges of Primary Parameter Used to Generate Condition Data

				Traffic Loading (million ESAL/Lane-yr)					
Environment	Surface Type	SNC	Surface Thickness	0.01	0.03	0.10	0.30	1.0	3.0
	AC	2	30	X		X			
		3	50	X		X		X	
		5	80		X		X		X
		8	100		X		X		X
DNF (0.005)	ST	2	12	X		X			
		3	12	X		X		X	
		4	15		X		X		X
		6	18		X		X		X
WNF (0.023)	AS FOR DNF ABOVE								
WF (0.100)	AS FOR DNF ABOVE								

Note: DNF = Dry, non-freeze; WNF = wet, non-freeze; WF = wet, freeze; ESAL = equivalent standard axle loadings (8,200 kg).

tiles, called "hinges," and the range (whiskers). Figure 2 is a box-and-whiskers plot of SNC (structural number modified for subgrade strength) without outliers, and Figure 3 is a box-and-whiskers plot of rut depth with an outlier. Although not all the outliers were erroneous, all were removed from the data before analysis because the data were only simulated, not from actual pavement conditions.

The Explorer software is a commercial ANN used in the modeling process. To use the software, the data inputs must be between 1 and 0. All the variables are divided by the maximum value in the generated data of the variable. Table 4 is a subset of data for a roughness prediction neural network. About 30 percent of generated data was used as an input, and about 10 percent was reserved for the set when networks were fully trained or had converged.

Training

The proposed scheme for roughness prediction involves the development of an ANN that could be trained to predict roughness of pavement, given pavement condition data. Initially three different architectures of the network were examined. The three had either one (48 PEs), two (24 PEs), or three layers (16 PEs), elements in keeping with a rule of thumb that requires a ratio of four hidden units for each input unit. The ANN training process depends mainly on the problem scale and the prediction accuracy required.

The back-propagation learning algorithm, also known as the generalized delta rule, was used in the learning process. In the back-propagation, each presentation of the data set and the input value (roughness) of the ANNs

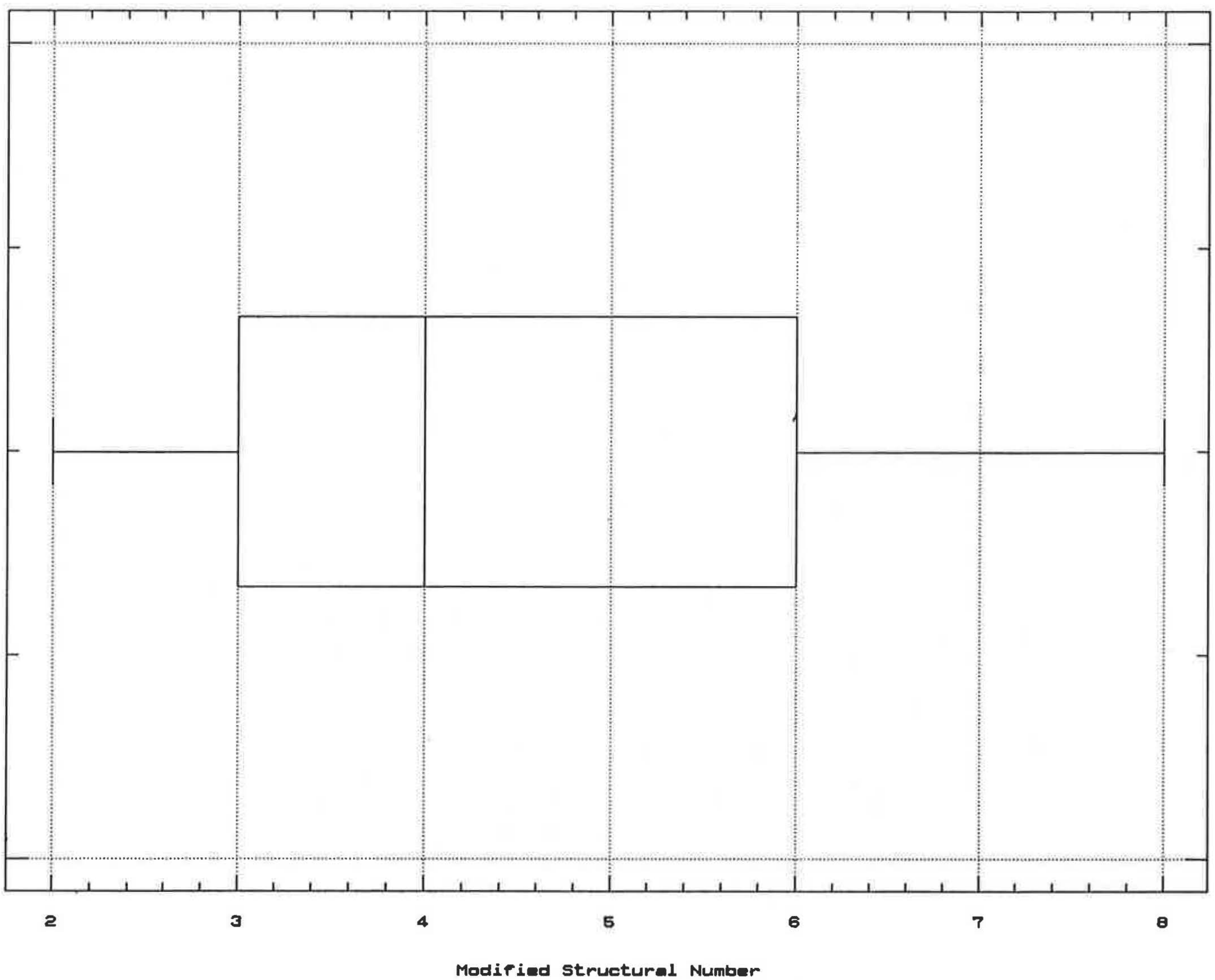

FIGURE 2 Box-and-whiskers plot of structural number modified for subgrade strength without outliers.

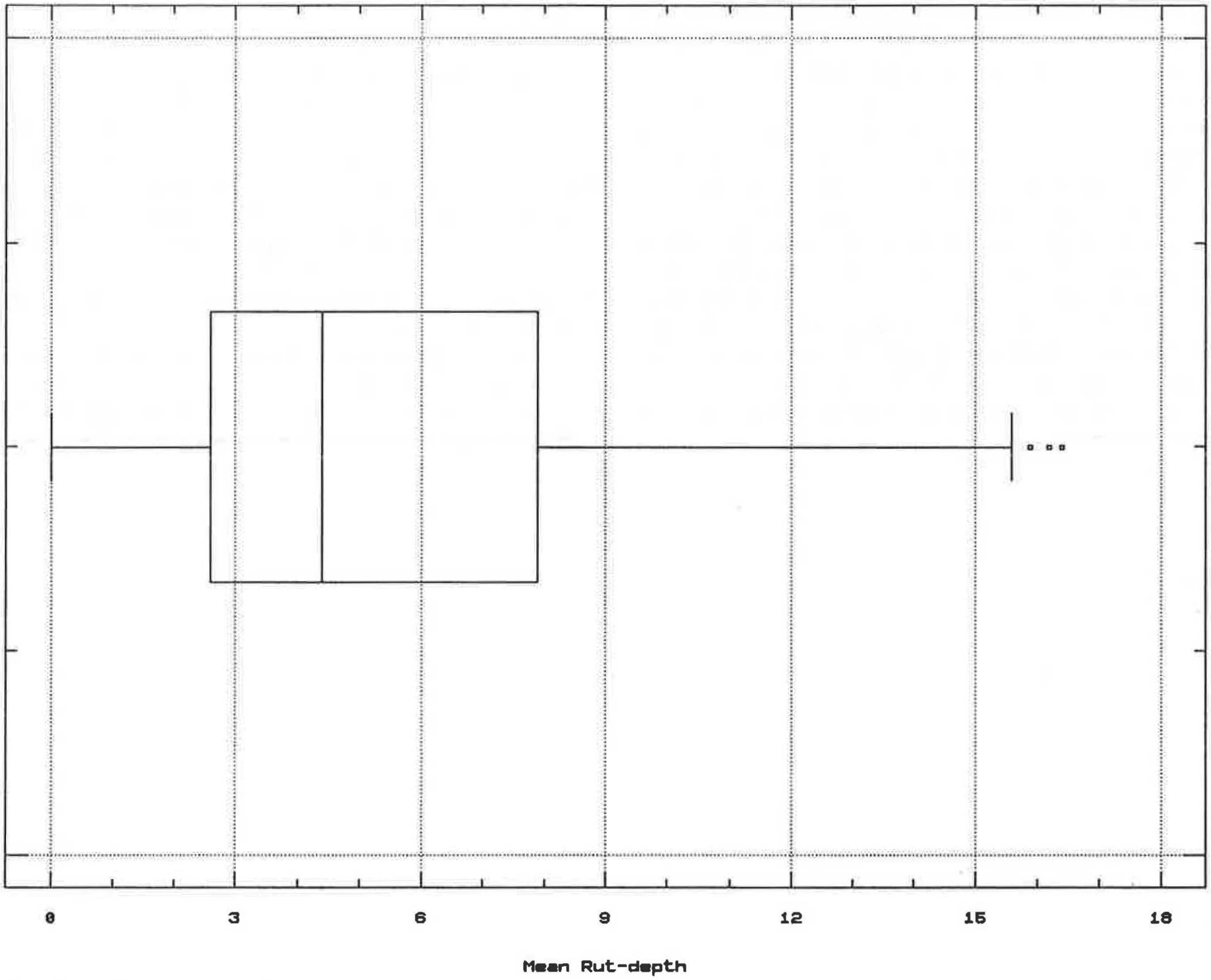

FIGURE 3 Box-and-whiskers plot of rut depth with an outlier.

are compared with desired output values and adaptive weights within the network and incrementally adjusted to minimize the output error. The sigmoid activation function was used. The inputs was compressed by the activation function into output values between 0 and 1. The back-propagation algorithm has demonstrated several advantages in addition to having the potential for determining networks with arbitrary mapping properties (*5*). Although the back-propagation learning method works, the learning process is very slow, even for fast computers (*6*).

The error function is expressed as

$$E = \frac{1}{2} \sum_{c} \sum_{j} \left[y_j(c) - d_j(c) \right]^2 \tag{2}$$

where

c = input sample case,
j = output node index,
y = actual output, and
d = desired output.

The overall objective is to minimize the error function by adjusting the interconnection weights. The training algorithm using back-propagation is well presented elsewhere. The initial weights and biases are chosen randomly. The adjusted weights and biases are as follows:

$$w_{ij}^{\text{new}} = w_{ij}^{\text{current}} - \eta \frac{\delta^t E_t}{\delta w_{ij}} + \alpha \left(w_{ij}^{\text{current}} - w_{ij}^{\text{previous}} \right) \tag{3}$$

$$\theta_i^{\text{new}} = \theta_i^{\text{current}} - \eta \frac{\delta^t E_t}{\delta \theta_i} + \alpha \left(\theta_i^{\text{current}} - \theta_i^{\text{previous}} \right) \tag{4}$$

TABLE 4 Example of Subset Data Used as Input for ANN Modeling

SNC	AADT	ESAL	AGE	CRA	CRW	CRX	RAV	PHA	RDM	RDS	PAT	RI
0.25	0.003	0.003	0	0	0	0	0	0	0	0	0	0.14
0.25	0.003	0.003	0.45	0.14	0.09	0.16	0.09	0	0.14	0.46	0	0.18
0.375	0.003	0.003	0.1	0	0	0	0	0	0.15	0.23	0	0.15
0.375	0.03	0.03	0	0	0	0	0	0	0	0	0	0.14
0.375	0.03	0.03	0.25	0	0	0	0	0	0.26	0.31	0	0.16
1	0.01	0.01	0	0	0	0	0	0	0	0	0	0.14
0.375	0.03	0.33	0.1	0.03	0	0.02	0	0	0.29	0.31	0	0.18
0.375	0.33	0.33	0.6	0.94	0.94	0.95	0.02	0	0.79	0.83	0.19	0.5
0.75	0.01	0.01	0.25	0	0	0	0	0	0.17	0.23	0	0.20
0.75	0.01	0.01	0.8	0.17	0.05	0.13	0.88	0	0.15	0.17	0	0.69
0.75	0.1	0.1	0.25	0	0	0	0	0	0.14	0.17	0	0.24
0.25	0.003	0.003	0	0	0	0	0	0	0	0	0	0.14
0.375	0.03	0.03	0.55	0.01	0	0.9	0.14	0	0.33	0.35	0	0.18
0.5	0.1	1	0.35	0.77	0.77	0.78	0.17	0	0.50	0.63	0.06	0.15
0.5	0.1	0.1	0.8	0.8	0.86	0.87	0.13	0	0.42	0.46	0.02	0.24
0.5	0.10	0.1	0.6	0.17	0.1	0.15	0.83	0	0.28	0.29	0	0.18
0.5	0.01	0.001	0.75	0.1	0.02	0.07	0.9	0	0.22	0.25	0	0.16
0.375	0.33	0.33	0.55	0.93	0.93	0.94	0.03	0	0.77	0.79	0.15	0.39

where α and η are learning rates. Back-propagation is accomplished in four steps:

Step 1: Normalized condition data generated by simulation are presented to the input layer.

Step 2: One pair of corresponding inputs (condition data) and the output (roughness) are presented.

Step 3: Using the actual roughness (output), the error with respect to given roughness is determined.

Step 4: Error is used to adjust the connecting weight.

Step 5: Using the next data pair, the process is repeated until "correct" roughness is obtained for all inputs used for training.

Result

During training the network result is compared with the correct result, and the mean-square error (MSE) is computed as follows:

Network Size	*Training Data*	*Training Cycles*
12-48-1	0.2	30,000
12-24-24-1	0.001	30,000
12-16-16-16-1	0.002	30,000

The MSE improves significantly as the number of hidden layers increases. It is difficult to evaluate the reliability of a newly trained network; inputs could be removed, added, or altered and the network retrained until the reliability of the network is established, according to Pratt et al. (6).

Figure 4 shows the relationship between actual roughness (from simulated data) progression and roughness predicted by ANNs. Between 2 and 7 IRI there is a fairly good correlation between the desired roughness and the roughness output from the ANNs. Above 7 IRI the ANNs model overestimates the roughness predictions. The R^2 obtained was 39.54 percent and the standard error of 1.88 IRI; 56 data points were used for the testing.

Concluding Remarks

The application of ANNs in pavement deterioration modeling is feasible when a large data base on pavement condition is available. This could form the basis for developing a generic intelligent pavement deterioration process. In the present studies, it seems that the back-propagation method was not too successful in training the fully connected ANNs with sigmoid activation functions.

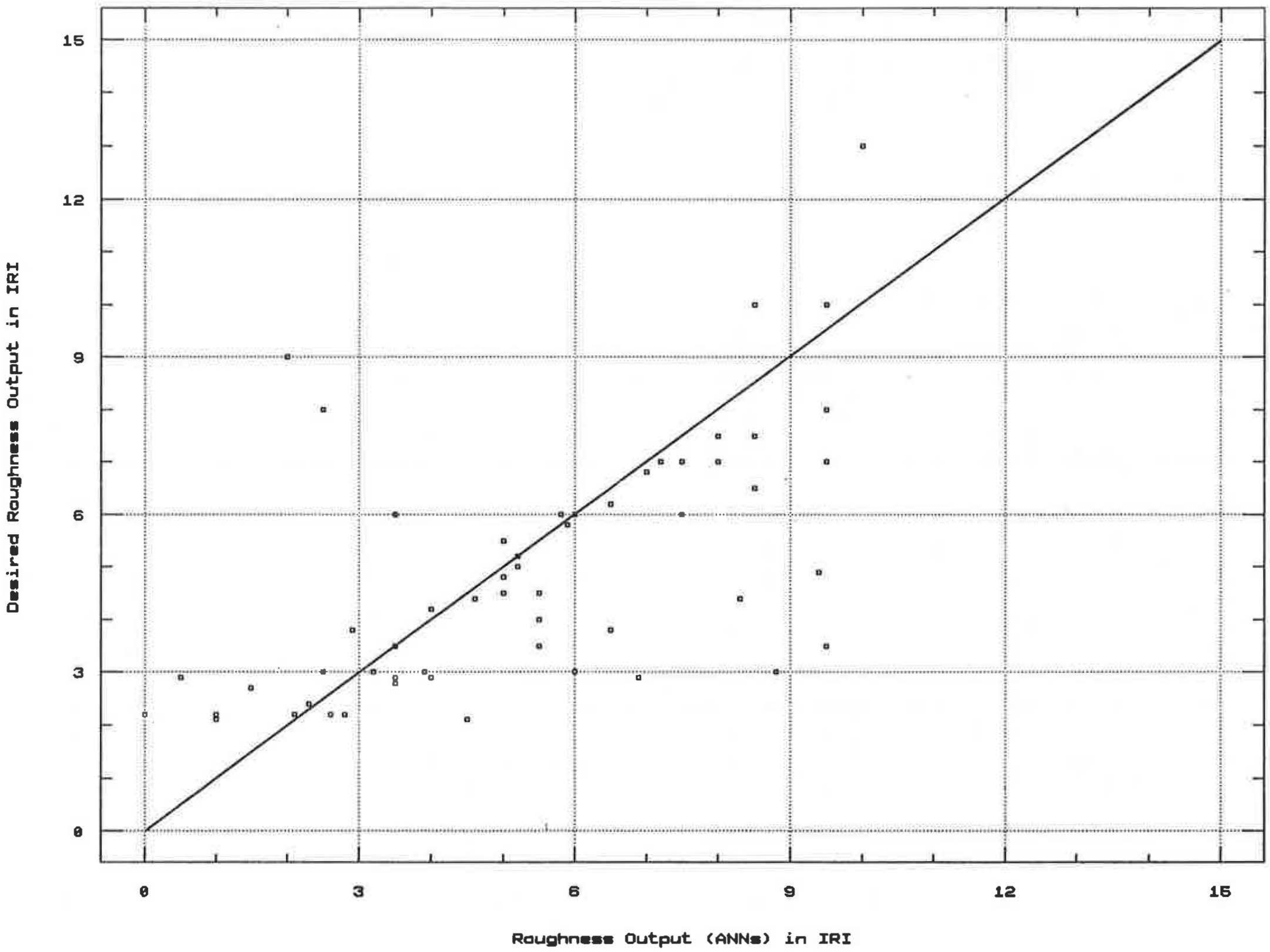

FIGURE 4 Plot of desired versus ANN roughness.

This might be because of the preprocessing of the input data. Furthermore, the commercial software used the applications has numerous in-build functions. Unfortunately, no rigorous method has been reported in the literature for selecting some of the in-build functions such as the learning rates. It will be important to explore whether different preprocessing of input data, learning rules, and transfer functions can perform more successfully. Testing was done using simulated data; it was recognized that this particular approach may not be general enough to perform well on other data sets, especially on in-service pavements. Furthermore, additional work is needed to identify which pavement condition variables can be used to accurately characterize roughness.

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