Feasibility of Using Artificial Neural Networks in Assessing Pavement Condition

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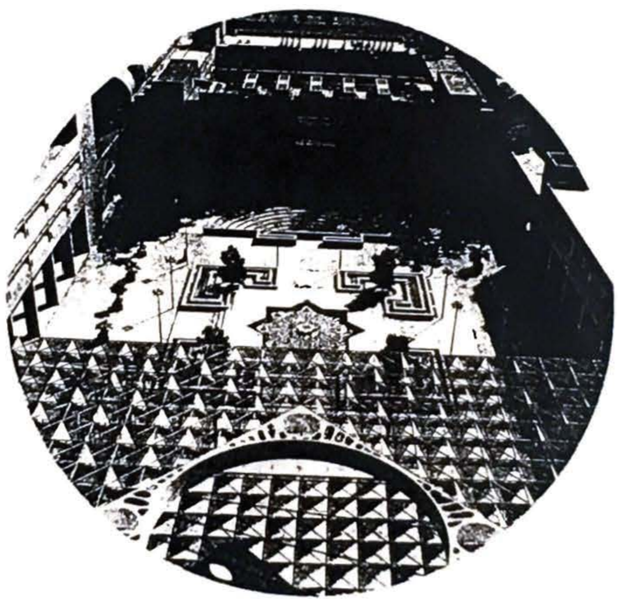

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A5 FEASIBILITY OF USING ARTIFICIAL NEURAL NETWORKS IN ASSESSING PAVEMENT CONDITION, A. A. Basma, Sultan Qaboos University, Al-Khoudh, SULTANATE OF OMAN and T.I. Al-Suleiman, United Arab Emirates University, Al-Ain, U.A.E. and M.T. Obaidat, Jordan University of Science and Technology, Irbid, JORDAN. [3.2]

A6 COMPARISON BETWEEN SWMM MODEL AND NEURAL NETWORK IN LEAST-COST STORM WATER SEWER SYSTEM DESIGN, M. Nouh, Sultan Qaboos University, Al-Khod, SULTANATE OF OMAN. [3.3]

14:30 - 15:30 **SESSION 2-B**	**CHAIRMAN : PROF. N. KAMIYA**
[HALL B]	

- **FINITE ELEMENT ANALYSIS II**

B4 NON-LINEAR FINITE ELEMENT ANALYSIS OF COMPOSITE BEAMS WITH PARTIAL - INTERACTION, A. Abdul Wali, University of Sana'a, Sana'a, REPUBLIC OF YEMEN. [4.4]

B5 VECTOR COMPUTATIONAL ALGORITHM FOR LAYERED RC SHELL ELEMENT STIFFNESS MATRIX, C-S. Min, Cheju National University, Cheju, KOREA. [4.6]

B6 FINITE ELEMENT ANALYSIS FOR MODULUS OF ELASTICITY ON POST-TENSIONED CLAY, CALCIUM SILICATE AND CONCRETE BLOCK MASONRY SECTIONS, S. H. Tapsir, University of Technology Malaysia, MALAYSIA. [8.1]

15:30 - 16:00 **TEA BREAK**

Proceedings of the Second International Conference in Civil Engineering on Computer Applications, Research and Practice

FEASIBILITY OF USING ARTIFICIAL NEURAL NETWORKS IN ASSESSING PAVEMENT CONDITION

A.A. BASMA — Sultan Qaboos University, Sultanate of Oman
T.I. Al-SULEIMAN — United Arab Emirates University, U.A.E.
M.T. OBAIDAT — Jordan University of Science and Technology, Jordan

Abstract

This paper investigates the feasibility of using artificial neural networks to model and predict pavement condition. Neural networks are information processing systems whose architecture simulates the biological structure of the brain. A simple back-propagation neural network was employed. Initially, the neural networks were trained using actual field data on several pavement sections. To ascertain the efficiency of the neural networks in assessing the pavement condition, as defined by the pavement condition index, PCI, both the number of input variables and hidden neurodes were varied. The model consisting of eight hidden neurodes and four input variables was found to be the most practical and successful. These variables were: sum of equivalent single axle load, surface thickness, base thickness and soil CBR. Comparison of forecasts made by the adopted prediction model demonstrated that neural networks are very reliable and simpler than conventional methods.

1. Introduction

One of the major and integral part of any pavement management system is the prediction of pavement performance. Additionally, and from a standpoint of the riding public, motorists as well as the highway departments and government agencies, pavement performance is critical. Pavement performance, as measured by highway engineers, involves the serviceability or condition of the pavement and the life to first resurfacing or reconstruction. Currently, there are several techniques to assess pavement serviceability or condition with most being either subjective in nature or empirical. They are generally based on information such as pavement distresses, pavement geometry and soil properties. Of these, the most commonly used are the Present Serviceability Index, PSI, and Pavement Condition Index, PCI. The former is measured on a scale of one to five whereas the latter is evaluated on a scale of 0 to 100. Newly constructed pavements generally have respective PSI and PCI values of 4.5 and 95; rehabilitation is mostly done anywhere between PSI values of 2.0-2.5 and PCI values of 40-60. These techniques, however, are in general time consuming and require a number of intermediary steps such as field inspections and measurements. Accordingly, developing other simple and relatively accurate yet practical methods to forecast the state of the pavement, becomes a necessity. This paper will attempt to suggest such a method. Essentially, the presented method is computer oriented and is modeled using the neural networks technology. It maps the basic inputs directly to the output without intermediary steps. Actual field data sets comprising of pavement condition, namely PCI values, and pavement characteristics, soil properties and traffic loading were collected and used to train and test the neural networks model. A complete description of the data base and the development of the neural networks model follow.

2. Development of Data Base

An accurate assessment of pavement condition must be based on a reliable and comprehensive data base. To accomplish the main objectives of this research, an integrated data base for pavement identification, pavement characteristics, traffic loading, and pavement condition was developed. The data base covered a total of 99 sections from primary rural and roads representing the different climatic conditions and geographic locations. A pavement section is defined as that portion of the road which has similar characteristics in terms of geometric configuration, traffic level, material properties, pavement age, and drainage system. The data utilized herein was collected from the following sources of information.

1. Ministry of Public Works and Housing (MPWH). The contract documents, construction and road maintenance records, and engineering studies in the MPWH were reviewed to extract the following data elements for each pavement section:
   a. Construction data or data of last major maintenance (overlay).
   b. Average daily traffic.
   c. Percentage of trucks.
   d. Thickness of different pavement layers.
   e. California Bearing Ratio (CBR) of

existing pavement layers and subgrade soil. It is worth while mentioning here that the variation was only found in soil strength.

2. Field inspection: The PAVER system, which was developed by the U.S. Army Corps of Engineers [1], was used in evaluating the condition of the selected pavement sections. The PAVER system requires the demarcation of the road network into manageable pavement sections for inspection purposes. This system provides the user with other important capabilities including data storage and retrieval, determination of present and future pavement condition, estimation of maintenance and repair needs, and performing economic analysis and budget planning. The Pavement Condition Index (PCI) was introduced in the PAVER system as an indicator of the pavement structural integrity and surface operational condition. This index is determined on a scale from 1 to 100, with 100 being excellent and it is estimated from a combination of distress types, severity and extent obtained during inspection. The PCI agrees closely with the collective judgement of experienced pavement engineers and has a high degree of repeatability. Further details concerning the calculation of PCI are presented elsewhere [2].

To investigate the effects of different vehicle types and weights on pavement condition, the equivalent 18-kips (80 kN) single axle load (W) was used. The following steps were taken to estimate the accumulated traffic loading (ΣW) for a given pavement section:

1. Pavement age was considered as the number of years since construction or last overlay.
2. For a given year, the W-value was obtained using the following formula:

$$W = ADT*PT*EALF*LDF*365 \qquad (1)$$

Where,

ADT = Average daily traffic.
PT = Percentage of trucks.
EALF = Equivalent axle load conversion factor.
LDF = Lane distribution factor (assumed to be equal to 0.55)

3. Step (2) was repeated for all years included in the pavement age. Then, the W values for these years were summed up to obtain ΣW since construction or last overlay. Alternatively, ΣW can be estimated by multiplying the mean annual W-values by the pavement age.

As can be noted from the aforementioned discussion, the conventional procedure of quantifying the PCI requires data collection of several variables and field inspections. This may prove to be tedious and time consuming. Consequently, introducing a simple and expedient yet accurate methodology such as artificial neural networks for estimating PCI becomes essential and the very order of things in this domain.

3. Definition of Artificial Neural Networks (ANNs)

Neural networks could be defined as information processing structures that consist of many simple processing elements; i.e. neurons, with dense parallel interconnections. The connections between the neurons are called synapses. Each neuron receives weighted inputs from many other neurons, and communicates its outputs to many other neurons. Thus, information is represented by across massive weighted neurons interconnections. ANNs might be single or multilayer. The single-layer ANNs present processing units of the ANNs which take inputs from the outside of the network and their outputs go to the outside of the network; otherwise the ANNs are considered as multilayers [3].

The basic methodology of ANNs work consists of three stages: network training, testing, and implementation. The neurons' weights are adjustable through the programming training process, while the training effect is called learning. The learning process is done by giving weights computed from a set of training data or by adjusting the weights according to a certain condition. For the purpose of this research work, a multi-layer ANN has been utilized using the structure shown in Fig. 1. Pavement characteristics, traffic parameters, and soil strength were the ANNs input, whereas a hidden layer of variable number of nodes was used in order to quantify the output node; i.e. the Pavement Condition Index (PCI).

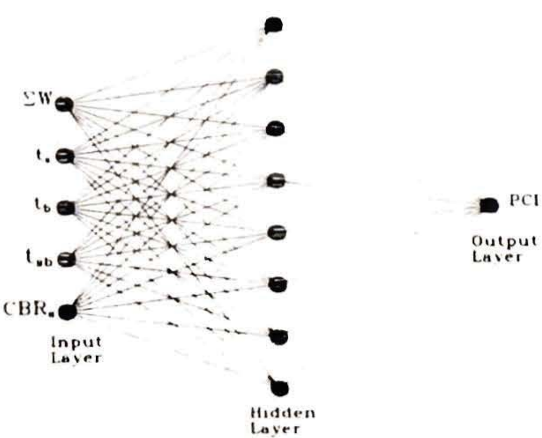

Fig. 1. Neural network structure

4. ANNs Application to Transportation Engineering

ANNs applications in the field of transportation engineering have grown rapidly nowadays, especially if compared with conventional Artificial Intelligence (AI). This is due to their promising potential in the areas which require optimal solutions in problems solving as well as problems dealing with uncertainty and randomness [4]. However, little practical research activities are available. Applications in trip generation forecasting, traffic delay, and volume prediction using back-propagation ANNs are recently reported in literature [6, 7, 3]. Whereas, building of intelligent system for automated pavement evaluation is still under development (Ratchie et al., 1991). Research work is focusing on the integration of advances of imaging with ANNs technology in order to assist quantifying the pavement evaluation process in real-time. Impressive potential of ANNs has been proven for pavement image processing for distress classification and quantification [8].

Consequently, neural networks could be successfully utilized for pavement serviceability evaluation as well as pavement condition evaluation, too. This paper explores the potential of ANNs in assessing pavement conditions in order to quantify the PCI using little information and ease-to-use prediction formula.

5. Neural Networks Modelling of Pavement Condition

Multiple regression techniques are commonly used to model complex relationships entailing several parameters. This is often complicated and ambiguous, especially for highly curvilinear functions. Furthermore, to formulate the regression model, the basic and influential variables must be known and available. In contrast, modelling by neural networks is more explicit because there is no need to designate a mathematical function relating the target or output variable to the causative or input variables. Neural networks are usually efficient enough to encapsulate intricate non-linear associations between input and output variables in a system. Additionally, they can infer appropriate reactions that spaciously represent the training data set. As part of their training process, neural networks allocate low connection weights to extraneous input variables which could be excluded from the model. In this study, the neural networks are initially trained to deal with innate noisy or ambiguous information using actual field collected data of PCI. Once the network was deemed fully trained, it prediction capability was tested against an additional set which it did not encounter previously. This is called the testing phase. No additional learning occurs during this phase.

The back-propagation neural network technique was employed in this investigation. In the first training cycle random connection weights were specified between neurodes and then continuously revised in successive cycles. The updating of the weights is governed by the selected learning rate η and the momentum factor α to enhance the efficiency of the learning process. Training was conducted repeatedly till the average sum squared errors SSEA over all training paradigms are reduced to a minimum. Here SSEA is evaluated as

$$SSEA = \frac{1}{N_p}\left[\sum_{i=1}^{i=N_p}(PCI_a - PCI_o)^2\right] \quad (2)$$

where N_p = Number of paradigms; PCI_a = actual field value of PCI; and PCI_o = neural network output value.

In order to evaluate the prediction quality of the network, a total of six models with varying inputs and hidden neurodes were tried. All of the analyses were performed with a momentum factor α = 0.08 and a learning rate η = 0.1. The optimal values of α and η, and the number of neurodes in the hidden layer were determined through trial and error. Training was conducted for a total of 100000 cycles or until the average sum squared error was minimized. Training time on a 80486-33 MHz personal computer was less than one hour.

6. Data Analysis

To determine the most reliable neural network model, two sets of runs were performed. In the first set, seven input variables (or neurodes) were used. These variables were: (a) cumulative equivalent single axle load, ΣW; (b) pavement age (AGE) in years; (c) surface thickness, t_s, in cm; (d) base thickness, t_b, in cm; (e) sub-base thickness, t_{sb}, in cm; (f) last overlay thickness, t_{ov}, in cm; and (g) subgrade CBR_s. Using these inputs, three models were considered namely M1, M2 and M3 with 4, 6 and 8 hidden neurodes, respectively. The output of the model M3 revealed that AGE, t_s, and t_{ov} have minimal effect on PCI with respective percent relative importance of 1.36%, 5.91% and 0.87%. Consequently, it was decided to omit AGE because it is implicitly included in ΣW and combine both t_s and t_{ov} to form the overall surface thickness. Using this latter parameter and the remaining variables, three additional models, M4, M5 and M6 respectively with 4, 6 and 8 hidden neurodes were tried. Fig. 2 shows a typical reduction of the average sum squared errors at various levels of the neural network training stage. As can be noted, the average sum squared errors were significantly reduced after about 30000 cycles. All of the models were found to converge in an almost similar fashion. From the output of the considered models, it was found that the number of neurodes in the hidden layer have a marked influence of the prediction performance of the neural networks.

Table 1 presents the training data set, the recalled values of PCI and the percent recall error for models M4, M5 and M6. Additionally, Table 2 lists the data used in the

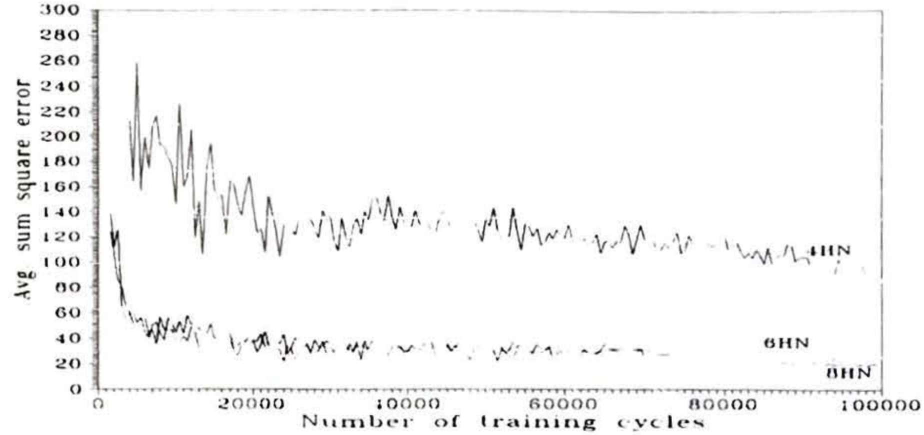

Fig. 2. Training progress of neural networks with 4, 6 and 8 hidden neurodes

Table 1. Input data and PCI values used for training Neural Networks

OBS	Input Data					PCI DATA	Recalled values with*			Percent error with		
	ΣW	t_s	t_b	t_{sb}	CBR_s		4HN	6HN	8HN	4HN	6HN	8HN
1	1369330	20.8	20	25	10	76.8	65.38	80.75	82.10	14.9	5.1	6.9
2	16308160	19.2	20	35	5	64.2	66.07	68.19	57.01	2.9	6.2	11.2
3	16308160	19.4	20	35	5	46.8	43.15	40.11	44.62	7.8	14.3	4.7
4	9082038	25.6	20	35	5	36.0	42.38	32.83	40.54	17.7	8.8	12.6
5	9082038	22.6	20	35	10	24.8	43.29	33.96	22.63	74.6	36.9	8.8
6	8699681	24.9	20	35	10	48.3	52.57	48.61	43.85	8.8	0.6	9.2
7	483775	19.6	20	20	10	79.0	85.13	84.57	86.60	7.8	7.1	9.6
8	403146	14.0	20	20	10	69.0	60.49	60.61	64.70	12.3	12.2	6.2
9	1773843	14.0	15	15	10	63.0	57.20	66.46	68.85	9.2	5.5	9.3
10	1773843	10.3	15	15	10	36.0	43.04	32.26	39.00	19.6	10.4	8.3
11	13918857	38.2	30	60	10	58.2	66.93	57.18	50.24	15.0	1.8	13.7
12	13918857	42.2	30	60	10	74.4	59.50	80.14	71.26	20.0	7.7	4.2
13	117154127	13.5	15	24	20	23.2	35.32	20.96	17.78	52.2	9.7	23.4
14	42435429	13.5	15	24	20	56.0	58.26	55.77	49.01	4.0	0.4	12.5
15	86597	19.6	25	30	10	56.0	44.30	50.28	50.88	20.9	10.2	9.1
16	865978	12.6	25	30	10	75.4	83.38	76.66	67.51	10.6	1.7	10.5
17	142632	18.5	25	30	10	84.2	72.69	80.90	76.35	13.7	3.9	9.3
18	277098	15.1	15	30	6	16.0	6.48	8.25	19.70	59.5	48.4	23.1
19	277098	15.1	15	35	8	24.6	41.52	21.07	31.19	68.8	14.3	26.8
20	277098	15.2	20	20	6	46.5	51.30	46.67	46.74	10.3	0.4	0.5
21	853209	15.2	20	20	6	77.6	82.02	70.24	76.10	5.7	9.5	1.9
22	853209	19.1	20	20	6	69.6	59.65	77.38	74.97	14.3	11.2	7.7
23	7452071	24.0	15	22	15	50.2	67.91	57.44	52.58	35.3	14.4	4.7
24	7452071	24.5	20	30	15	58.6	52.73	53.80	64.10	10.0	8.2	9.4
25	745071	23.9	20	30	15	40.4	31.65	32.03	39.86	21.7	20.7	1.3
26	745071	24.0	20	30	15	51.0	35.65	51.33	53.93	30.1	0.6	5.7
27	745071	25.0	20	30	15	54.0	53.99	54.46	55.87	0.0	0.9	3.5
28	612175	17.5	20	20	10	75.9	87.85	68.37	71.32	15.7	9.9	6.0
29	1344792	17.9	20	20	10	78.7	61.47	70.53	79.87	21.9	10.4	1.5
30	16675655	24.4	15	25	10	36.2	25.39	29.84	37.53	29.9	17.6	3.7
31	16675655	24.2	15	15	10	37.4	30.82	46.47	41.84	17.6	24.3	11.9
32	126448	5.5	15	20	20	65.8	66.68	62.85	72.56	1.3	4.5	10.3
33	115560	23.0	15	20	20	83.0	67.43	75.66	90.41	18.8	8.8	8.9
34	43356	19.0	15	20	20	92.8	79.21	87.58	87.25	14.6	5.6	6.0
35	43556	17.0	15	20	20	88.2	93.63	85.36	89.75	6.2	3.2	1.8
36	17605	17.2	15	20	20	81.8	83.75	85.44	89.28	2.4	4.4	9.1
37	13705	17.0	15	20	20	70.0	86.40	62.43	70.19	23.4	10.8	0.3
38	315858	31.5	15	20	20	67.2	56.00	65.66	70.01	16.7	2.3	4.2
39	62370	26.5	15	20	20	78.0	88.13	78.40	78.87	13.0	0.5	1.1
40	230410	17.0	20	20	15	87.0	70.00	95.09	86.39	19.5	9.3	0.7
41	29639	22.0	20	20	15	90.0	81.34	87.07	97.37	9.6	3.3	8.2
42	2517073	15.7	15	20	15	67.7	83.24	58.74	71.01	23.0	13.2	4.9
43	4345771	6.0	20	20	15	80.8	76.27	84.86	86.16	5.6	5.0	6.6
44	8182529	25.4	15	20	10	26.5	21.63	35.39	27.09	18.4	33.5	2.2
45	8182529	22.1	15	20	10	70.3	57.99	67.73	65.38	17.5	3.7	7.0
46	5659220	26.4	15	20	10	73.3	88.94	75.60	76.88	21.3	3.1	4.9
47	6142444	25.8	15	20	10	71.8	74.04	76.19	66.99	3.1	6.1	6.7

* HN = Hidden Neurodes

Table 2. Input data and PCI values used for testing Neural Networks

OBS	Input Data ΣW	t_s	t_b	t_{sb}	CBR_s	PCI DATA	Predicted values with 4HN	6HN	8HN	Percent error with 4HN	6HN	8HN
48	1369330	20.8	20	25	10	75.4	74.07	80.79	83.71	1.76	7.15	11.03
49	16308160	31.8	20	35	5	54.0	50.33	61.29	47.91	6.80	13.51	11.28
50	9082038	20.9	20	35	5	58.6	37.38	48.92	36.07	36.21	16.52	38.45
51	9082038	25.6	20	35	10	50.7	38.96	36.02	28.13	23.16	28.96	44.52
52	483775	19.6	20	20	10	74.6	97.91	68.36	65.40	31.25	8.36	12.33
53	1773843	14.0	15	15	10	77.0	49.87	66.46	71.79	35.23	13.68	6.77
54	13918857	23.0	30	60	10	70.6	46.36	58.32	79.94	34.33	17.40	13.22
55	13918857	42.2	30	60	10	78.6	73.87	70.94	82.72	6.01	9.75	5.25
56	117154127	13.5	15	24	20	43.4	34.05	44.90	31.53	21.55	3.46	27.35
57	865597	21.1	25	30	10	49.0	48.21	42.42	44.02	1.62	13.43	10.15
58	86597	18.9	25	30	10	49.4	66.46	51.85	54.21	34.53	4.96	9.73
59	86597	19.6	25	30	10	61.4	71.58	68.75	60.74	16.58	11.98	1.07
60	86597	19.6	25	30	10	44.2	38.01	41.04	47.74	14.01	7.14	8.00
61	86597	12.7	25	30	10	34.0	45.51	28.67	34.14	33.85	15.67	0.41
62	142632	18.5	25	30	10	85.0	88.64	76.04	81.49	4.28	10.54	4.13
63	277098	15.1	15	35	8	24.0	27.38	21.87	24.64	14.10	8.86	2.67
64	277098	12.4	15	35	8	39.2	24.81	33.86	42.06	36.72	13.62	7.29
65	277098	15.2	20	20	6	54.0	39.80	63.40	50.27	26.29	17.40	6.90
66	7452071	28.1	15	22	15	54.0	34.27	46.92	52.71	36.54	13.12	2.39
67	7452071	23.8	15	22	15	43.0	46.95	47.18	46.27	9.18	9.72	7.59
68	7452071	23.8	20	30	15	48.4	44.79	41.12	48.07	7.45	15.04	0.68
69	745071	24.0	20	30	15	53.4	59.93	57.55	50.25	12.23	7.76	5.90
70	612175	18.5	20	20	10	86.3	95.85	89.07	93.87	11.06	3.21	8.78
71	612175	18.5	20	20	10	89.2	64.80	96.64	89.87	27.35	8.34	0.76
72	612175	18.5	20	20	10	83.9	88.80	69.48	74.59	5.84	17.19	11.10
73	612175	17.4	20	20	10	84.0	91.64	80.46	82.02	9.10	4.21	2.36
74	16675655	23.4	15	15	10	34.0	42.44	31.70	29.61	24.82	6.75	12.91
75	16675655	24.4	15	15	10	30.4	37.64	25.38	29.26	23.80	16.50	3.76
76	16675655	24.2	15	25	15	60.6	81.49	68.46	67.48	34.48	12.98	11.35
77	126448	5.0	15	20	20	54.8	51.05	47.03	56.58	6.83	14.18	3.25
78	115560	5.0	15	20	20	80.4	84.01	67.41	84.33	4.49	16.16	4.89
79	43556	19.0	15	20	20	85.2	93.00	89.80	93.25	9.15	5.40	9.45
80	17605	15.0	15	20	20	77.8	93.05	90.37	81.44	19.60	16.16	4.68
81	13705	15.0	15	20	20	80.2	55.82	70.18	86.44	30.40	12.49	7.77
82	315858	33.0	15	20	20	69.0	81.88	60.92	76.52	18.66	11.71	10.90
83	230410	17.5	20	20	15	91.4	79.34	76.18	84.84	13.20	16.65	7.17
84	414756	13.5	15	20	15	38.9	25.39	36.96	38.16	34.74	4.99	1.91
85	414756	13.5	15	20	15	35.5	25.86	38.67	38.86	27.16	8.93	9.45
86	139091	13.5	15	20	15	66.3	91.24	68.41	76.84	37.62	3.18	15.89
87	139091	11.8	15	20	15	61.5	55.10	53.78	63.50	10.41	12.55	3.25
88	2517073	11.8	15	20	15	56.8	75.65	55.85	56.31	33.19	1.67	0.86
89	2517073	15.7	15	20	15	59.4	81.22	54.17	66.06	36.73	8.80	11.21
90	1940640	15.5	20	20	14	90.0	65.78	90.95	82.16	26.91	1.05	8.71
91	4345771	6.8	20	20	15	89.6	77.10	98.27	77.12	13.95	9.68	13.93
92	8182529	27.0	15	20	10	61.5	84.62	62.52	65.88	37.59	1.65	7.12
93	8182529	27.0	15	20	10	59.8	46.11	69.68	59.98	22.89	16.53	0.30
94	8182529	27.0	15	20	10	67.3	53.37	63.53	66.35	20.70	5.60	1.41
95	8182529	25.4	15	20	10	36.1	39.15	39.33	38.22	8.44	8.95	5.87
96	8182529	25.4	15	20	10	25.8	20.34	21.76	25.88	21.16	15.65	0.30
97	8182529	22.1	15	20	10	45.7	53.90	40.08	48.05	17.94	12.31	5.13
98	5659220	27.3	15	20	10	69.3	47.22	77.70	78.24	31.86	12.13	12.90
99	6142444	26.4	15	20	10	60.8	60.05	53.08	69.96	1.24	12.69	15.06

testing phase and the predicted values of PCI by the same models as before. Suffice it to point out that this latter table demonstrates that although the neural networks were not explicitly trained for these data, they were proficient enough to recognize specific paradigms and gave plausible predictions. Table 3 summarizes the performance of the neural network models considered. The results indicate that all models were successful in learning the relationship between the input and output data with variable degrees. The best performing model was M3, with seven inputs variables and eight hidden neurodes. In comparison, model M6 with five input variables showed a minimal reduction in performance quality thus making this model, for practical purposes, more appealing. To further validate the accuracy of model M6, Fig. 3 was prepared. This figure shows a plot of the measured values of PCI versus the recalled values (training phase) and the predicted values (testing phase) of PCI by model M6. The correlations between the aforementioned PCI values and their regression equations are shown in Table 4. Table 5 shows the weights of the input-hidden layer connections, an the hidden-output layer connections, for model M6. Partitioning of the hidden-output connection weights into components connected with the input neurodes [9] was conducted and are listed in Tables 6 and 7. The following gives calculation procedure for the neural networks of model M6:

1. For each hidden neurode i, multiply the absolute value of the hidden-output layer

Table 3. Comparison of SSE and percent errors of neural network modes

Model	Input Variables*	HN@	Avg. SSE		Avg. %Err.		Overall Avg.	
			Train	Test	Train	Test	SSE	%Err.
M1	ΣW, AGE, t_s, t_b, t_{sb}, t_{ov}, CBR_s	4	90.9	196.2	15.3	19.3	145.9	17.4
M2	ΣW, AGE, t_s, t_b, t_{sb}, t_{ov}, CBR_s	6	24.2	48.9	9.2	10.1	37.2	9.7
M3	ΣW, AGE, t_s, t_b, t_{sb}, t_{ov}, CBR_s	8	18.8	45.3	7.8	9.2	32.6	8.5
M4	ΣW, t_s, t_b, t_{sb}, CBR_s	4	93.2	204.2	18.5	20.5	151.5	19.6
M5	ΣW, t_s, t_b, t_{sb}, CBR_s	6	24.8	55.8	9.6	10.9	41.1	10.3
M6	ΣW, t_s, t_b, t_{sb}, CBR_s	8	19.0	50.6	7.7	8.7	35.6	8.2

* ΣW = Sum of equivalent single axial load; AGE = Pavement age, years; t_s = Surface thickness, cm; t_b = Base thickness, cm; t_{sb} = Subbase thickness, cm; t_{ov} = Last overlay thickness, cm; CBR_s = Soil CBR.
@ HN = Number of hidden neurods

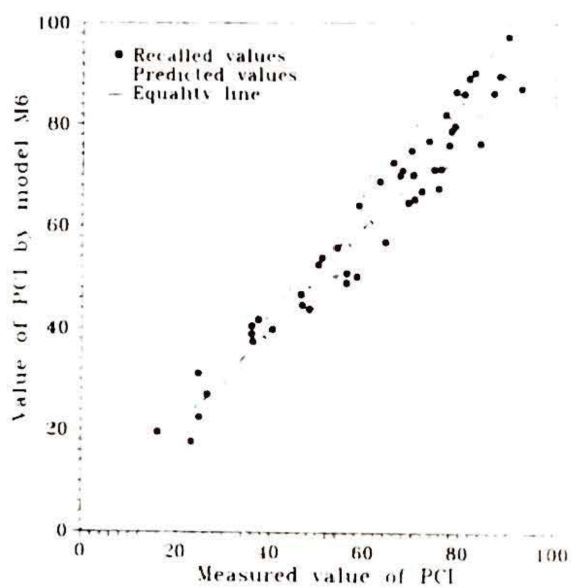

Fig. 3. Recall and predicted values of PCI by neural networks in comparison with measured values

connection weight by the absolute value of the input-hidden layer connection weight. Repeat this process for all input variables j. The products P_{ij} are listed in Table 6. As an example, $P_{23} = 2.569*1.277 = 3.281$.

2. For each hidden neurode, divide P_{ij} by the sum over all the input variables to obtain Q_{ij}. For instance, $Q_{21} = P_{23}/(P_{21}+P_{22}+P_{23}+P_{24}+P_{25}) = 0.277$

3. For each input neurodes, sum the values of Q_{ij} over all hidden neurodes to give S_j. For example $S_1 = Q_{11} + Q_{21} + Q_{31} + Q_{41} + Q_{51} + Q_{61} + Q_{71} + Q_{81} = 2.335$.

4. Divide S_j by the sum of S_j over all input neurodes. This ratio, expressed as a percentage, gives the overall relative importance or effect of each input variable on the output. For example, the percent relative importance of input variable 3 (base thickness, t_b) is $R_3 = (S_3 \times 100\%)/(S_1 + S_2 + S_3 + S_4 + S_5) = 29.19\%$. The computed values for all inputs are listed in Table 7.

For Model M6, the results indicate that the most important input factor is base thickness followed by soil CBR, sub-base thickness, sum of equivalent single axial load and surface thickness. This explains why the difference in the performance of models M3 and M6 is minimal. Model M6, without the pavement age and with a combined total surface thickness equals to the initial surface thickness plus the overlay thickness, had almost the same percent prediction error in both the training and testing phases in comparison to model M3.

7. General comments

The neural networks modeling technique is simpler to implement than other methods for assessing pavement condition. Basically to obtain the pavement condition index, PCI, only minor processing of the data for a given set of easily accessible input variables such as traffic information, pavement characteristics and soil strength properties, is necessary. In comparison, other methods

Table 4. Regression of calculated values of PCI on target values

Phase	n	Regression Equation	r^2	SEE
Training	47	$PCI_a = 2.73 + 0.95\ PCI_o$	0.95	4.76
Testing	52	$PCI_a = 8.32 + 0.86\ PCI_o$	0.87	6.71
Training and Testing	99	$PCI_a = 5.64 + 0.91\ PCI_o$	0.91	5.88

n = number of data points; PCI_a = actual or target value of PCI; PCI_o = output or calculated value of PCI;
r^2 = coefficient of simple determination; SEE = standard error of estimate

Table 5. Connection Weights for Model M6

Hidden neurodes	j = 1 ΣW	2 t_a	3 t_b	4 t_{ab}	5 CBR_s	Output
i = 1	-2.076	0.860	-3.802	-0.397	-0.899	4.827
2	-2.884	-0.715	-2.569	1.284	1.834	-1.277
3	1.964	0.904	2.316	-1.370	2.038	4.906
4	-0.588	-0.274	-6.324	-3.109	0.094	1.836
5	0.965	0.023	0.549	3.177	4.112	-3.396
6	0.873	-0.145	-0.837	0.999	3.798	4.790
7	-2.159	0.825	-3.792	-1.459	-4.517	-0.268
8	0.461	-0.580	1.420	3.154	-0.791	1.412

Table 6. Products P_{ij} for Model M6

Hidden neurodes	j = 1 ΣW	2 t_a	3 t_b	4 t_{ab}	5 CBR_s
i = 1	10.019	4.153	18.352	1.914	4.341
2	3.683	0.912	3.281	1.639	2.341
3	9.637	4.436	11.363	6.724	10.001
4	1.080	0.503	11.613	5.709	0.172
5	3.278	0.079	1.865	10.789	13.963
6	4.184	0.696	4.012	4.785	18.194
7	0.579	0.221	1.018	0.392	1.212
8	0.651	0.819	2.005	4.453	1.117

Table 7. Values of Qij for Model M6

Hidden neurodes	j = 1 ΣW	2 t_a	3 t_b	4 t_{ab}	5 CBR_s
i = 1	0.258	0.107	0.473	0.049	0.112
2	0.311	0.077	0.277	0.138	0.197
3	0.229	0.105	0.270	0.159	0.237
4	0.057	0.026	0.609	0.299	0.009
5	0.109	0.003	0.062	0.360	0.466
6	0.131	0.022	0.126	0.150	0.571
7	0.169	0.065	0.297	0.114	0.354
8	0.072	0.090	0.222	0.492	0.124
Sum S_j	1.336	0.495	2.335	1.763	2.070
% Relative importance	16.70	6.19	29.19	22.04	25.88

may require large number of data with some dictating field measurements. Nevertheless, one major reproof of the neural networks is its inability to track and interpret the step-by-step logic it employs to reach at the target outputs from the furnished inputs. This drawback, however, is expected to be surmounted with additional research.

8. Summary and conclusions

The work presented herein utilizes neural networks technology to model and predict the pavement condition using actual field data. By using such a technology, the final model is said to have encapsulated the data sets in such a way that very little prior assumption about the relationship between the data attributes is needed. As long as the important parameters are present in the data analyzed, the training process will enhance the most fundamental relationship(s) on the model's long term memory. Any combination of the data attributes will invoke the appropriate reaction from the memory. Input data that are insignificant will be ignored or given low connection weights and, consequently, will have low relative importance. The final proof of applicability of the neural networks model is provided through its ability to predict output values from data which it had never encountered.

Based on the results of this investigation, it was concluded that the performance of the neural networks used to model pavement condition improved with both the number of input variables and number of hidden neurodes. However, for practical purposes, the model including the equivalent single axle load, surface thickness, base thickness, sub-base thickness, and subgrade CBR, as input variables with eight hidden neurodes was found to be very successful in predicting PCI values.

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