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Artificial Neural Network (ANN) Based Pavement Deterioration Models for Low Volume Roads in India

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Abstract: The timely identification of undesirable distresses has been a critical step in pavement management at the network level. To date, many models have been developed to forecast pavement conditions. The most popular model in developing countries is the World Bank developed model: HDM-4. This study summarizes the implementation of a pavement condition prediction methodology using the Artificial Neural Network (ANN) to forecast cracking, raveling, rutting and roughness for Low Volume Roads (LVR) in India. Road inventory data, as well as six cycles of pavement performance data that include distresses, subgrade characterization and traffic data, were collected from 61 in-service LVR pavement sections over a 3 year period in India. ANN models with different architectures were trained and tested to suggest the optimum ANN model. The study results suggest that ANN models satisfactorily forecast future individual distresses. The performance of the suggested ANN models is also compared to the calibrated HDM-4 models.

Key words*: ANN; Deterioration; Distress; HDM-4; LVR.*

Introduction

Artificial neural networks use the mathematical simulation of biological nervous systems to process acquired information and derive predictive outputs after the network has been properly trained for pattern recognition. A neural network consists of numerous layers of parallel processing elements, or neurons. One or more hidden layers may exist between an input and output layer. The neurons in the hidden layers are connected to the neurons of a neighboring layer by weighting factors that are adjustable during the model training process. The networks are organized according to training methods for specific applications. Fig. 1 illustrates a typical three-layer neural network consisting of four neurons in the input layer, four neurons in the hidden layer, two neurons in the output layer, and interconnecting weighting factors (w_{ij}) between the layers of neurons.

The "training" of an ANN model is a procedure by which ANN repeatedly processes a set of test data (input-output data pairs), changing the values of its weights according to a predetermined algorithm in order to improve its performance. Back-propagation is the most popular algorithm for training ANN models (Lippman, 1987) [1]. It is a supervised learning method in which an output error is fed backward through the network, altering connection weights so to minimize the error between the network output and the targeted output. The following equation is used for correcting the weighting factor:

$$\Delta w_{ij}(n) = \alpha \Delta w_{ij}(n-1) - \varepsilon(\partial E / \partial w_{ij}) \tag{1}$$

where $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are weight increments between nodes i and j during the nth and $(n-1)$th steps. The momentum factor α is used to speed up the training in flat regions of the error surface and helps to prevent oscillations within the weights. A learning rate (ε) is used to decrease the potential of the training process being trapped in local minima instead of global minimal.

Background Literature

ANNs are valuable computational tools that are increasingly being used to solve complex, resource-intensive problems as an alternative to using more traditional techniques. Ceylan et al. (2004) used ANNs as pavement structural analysis tools for the rapid and accurate prediction of critical responses and deflection profiles of flexible pavements subjected to typical highway loadings [2]. Meier et al. (1997) trained back propagation type ANNs as surrogates for ELP analysis in a computer program for back calculating pavement layer moduli and realized a 42 times increase in processing speed [3]. Gucunski and Krstic (1996) [4] and Khazanovich and Roesler (1997) [5] reported similar ANN applications. The research project team working on the development of the new, mechanistic based AASHTO Pavement Design (NCHRP 1-37A) has recognized ANN as nontraditional yet possessing very powerful computing

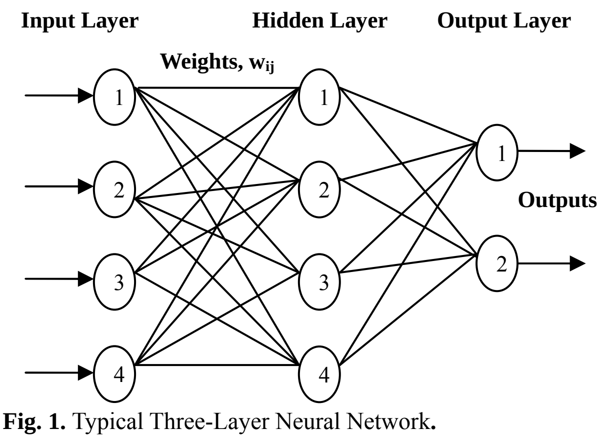

Fig. 1. Typical Three-Layer Neural Network**.**

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techniques, taking advantage of ANN models in preparing the 2002 Design Guide concrete pavement analysis package.

In addition, artificial neural networks (Attoh-Okine, 1994, 1999, 2001, 2002 [6-9]; Choi, Adams, and Bahia, 2004 [10]; Sundin and Braban-Ledoux, 2001 [11]; Roberts and Attoh-Okine, 1999 [12]; Alsugair and Al-Qudrah, 1998 [13]; Huang and Moore, 1997 [14]; Fwa and Chan, 1993 [15]) have recently been used in simulating pavement deterioration, pavement-performance prediction, flexible pavement cracking prediction, and condition ratings of jointed concrete pavements. Several neural network studies, as explained above, have been conducted to estimate current pavement condition, predict future pavement deterioration, and finally assist engineers in selecting optimal maintenance and rehabilitation activities. Such applications will help pavement management engineers to choose the best available resource allocation strategies. Thube (2006) [16] and Thube et al. (2006) [17] attempted to suggest ANN based pavement deterioration models for low volume roads in India by using the sigmoid axon function for training ANN models.

Objective of the Study

The objectives of the present study are as follows:

(i) To suggest an appropriate ANN model to predict the progression of different pavement distresses such as total cracking area, total raveling area, rut depth and roughness for low volume roads in different terrains of India.

(ii) To compare distress predictions for low volume roads in India made by the proposed ANN models against predictions made by the calibrated HDM-4 models.

Methodology of the Development of ANN Models

In this study, individual unified ANN models are developed to predict the value of progression in total cracking area (in percentage), in total raveling area (in percentage), in rut depth (in mm), and in total roughness (in IRI) for flexible LVR pavement sections. Sixteen different types of ANN architectures were used for each type of distress to determine the best ANN model architecture. The back propagation algorithm, which is the most commonly used type of artificial neural network, is used to train neural networks. The details for identifying various input parameters for model development, a database selection for training, testing and validation, and the training and testing of ANN models are discussed next.

Identification of Input and Output Variables

From the analysis of the performance model equations in HDM-4 models (Odoki, 2000) [18], it is evident that the pavement's evolution fundamentally depends on four global variables: traffic, pavement age (calculated from the date of construction or most recent rehabilitation), dominant climatic conditions, and structural capacity. These variables help to define the initiation as well as the progression of the distress. They may exhibit together with interaction between the different manifestations of damage and wear.

Road inventory details, as well as six cycles of pavement performance data (pre-monsoon, post-monsoon, and during the winter season) that include various pavement distresses, sub-grade characterization, and traffic data, are collected from 61 in-service LVR pavement sections located in the Uttarakhand state of India during the years 2004, 2005, and 2006. The data were subsequently used for the calibration of HDM-4 models and the development of ANN models. Shown in Table 1, the category of input variables for proposed different ANN models are selected primarily on the basis of corresponding HDM-4 pavement deterioration models and the details of input variables for each individual ANN model. The input variables for ANN models consisting of traffic data, climatic or environmental details, road geometry class, pavement details including that of subgrade, pavement distress data, etc., for each of the identified road section have been collected from field studies as well as from the office records of highway divisions in charge of the maintenance of these roads.

The types and extent of distresses (e.g. areas of cracking, raveling, pothole and edge break) have been measured by experts experienced in this area through visual surveys of each road test section. These surveys are done by making the affected areas in the form of geometric shapes having similar distresses. The corresponding ANN model outputs will include total cracking area (%), total raveling area (%), total rut depth progression (mm), and total roughness progression (IRI). The details of the general characteristics of the data sets used for the development of ANN models in the present study are given in Table 2. Similarly, HDM-4 pavement deterioration models have been calibrated for LVR in accordance with Indian conditions by using the above periodic performance data sets. The details of the suggested HDM-4 calibration coefficients are given in Table 3 [18].

ANN Model Architecture

The selection of ANN architecture is not a decision making process. Most of the time, trial and error, combined with engineering judgment, is used to determine the appropriate architecture for a particular problem. In the present study, a number of input and output variables are kept constant, and variations are made in the hidden layers and in the neurons per hidden layers. The details of the sixteen different ANN model architectures used for each cracking, raveling, rut depth, and roughness progression ANN model in the present study are given in Table.4.

Training and Testing Set Generation

The task known as the formation of datasets is carried out with the objective of forming three datasets that can be instantaneously used for network training, testing, and validation. The database is divided into two datasets, and the first set includes all of the historical pavement performance information except the last cycle, which has been used for training/testing purposes. The second dataset contains only the latest cycle data, which has been used for validation purposes. To obtain the training and testing datasets, the whole dataset used for training and testing purposes is again divided into two subsets. One set contains 80% of the data that are used for network training, and the remaining set contains 20% of the data used for network testing. According to the database

Table 1. Details of Input Variables for ANN Model Developments.

Serial No.	Details of Input Variables	Details of ANN Model: Cracking Progression Model	Raveling Progression Model	Rut Depth Progression Model	Roughness Progression Model
1	Age in Months	✓	✓	✓	✓
2	Initial Cracking Area (% Area) at Start of Analysis Cycle	✓			
3	LL of Subgrade	✓	✓	✓	✓
4	PL of Subgrade	✓	✓	✓	✓
5	PI of Subgrade	✓	✓	✓	✓
6	Field Moisture Content of Subgrade	✓	✓	✓	✓
7	OMC of Subgrade	✓	✓	✓	✓
8	CBR (Soaked) of Subgrade	✓	✓	✓	✓
9	Maximum Dry Density of Subgrade	✓	✓	✓	✓
10	SNP	✓	✓	✓	✓
11	AADT (Motorized)	✓	✓	✓	✓
12	AADT (Non-motorized)	✓	✓	✓	✓
13	% of Truck Volume	✓	✓	✓	✓
14	Composition of Commercial Vehicles (%)	✓	✓	✓	✓
15	Percentage Duration of Dry Season	✓	✓	✓	✓
16	Mean Monthly Precipitation (mm)	✓	✓	✓	✓
17	Mean Annual Temperature (Degrees)	✓	✓	✓	✓
18	Average Temperature Range (Degrees)	✓	✓	✓	✓
19	No of Days Having Temperature > 32 ^{0}C	✓	✓	✓	✓
20	Rise + Fall (m/km)	✓	✓	✓	✓
21	Horizontal Curvature (Degree/km)	✓	✓	✓	✓
22	Speed Limit (km/h)	✓	✓	✓	✓
23	No of (Rise + Fall) / km	✓	✓	✓	✓
24	CDS(Construction Defects Indicator for Bituminous Surfacing)	✓	✓	✓	✓
25	CDB(Base Construction Defects Indicator)	✓	✓	✓	✓
26	CRP(Cracking Progression Retardation Indicator)	✓	✓	✓	✓
27	Initial Raveling Area (% Area) at Start of Analysis Cycle		✓		
28	Observed Cracking Area (%) During Present Cycle			✓	✓
29	Observed Raveling Area (%) During Present Cycle			✓	✓
30	Observed Potholing area (%) During Present Cycle			✓	✓
31	Observed Rut Depth (in mm) During Present Cycle			✓	✓
32	Observed Edge Break (in sq. m) During Present Cycle				✓
33	Observed Roughness (IRI) at Start of Analysis Cycle				✓
Total Input Variables for ANN Model		26	26	29	31

Table 2. Characteristics of the Database for ANN Model Development.

Serial No.	Description of Variable	Details of Database: Minimum	Maximum	Range
1	Age in Months	12	260	248
2	Adjusted Structural Number of Pavement Section(SNP)	1.46	2.78	1.32
3	Motorized AADT	40	1507	1467
4	Non-Motorized AADT	8	1194	1186
5	Total Cracking Area (%)	0	41.47	41.47
6	Total Raveling Area (%)	0	68.81	68.81
7	Edge Break Area (sq. m)	0	51.86	51.86
8	Total Rut Depth(in mm)	3	22	19
9	Total Pothole Area (%)	0	0.147	0.147
10	Total Roughness(in IRI)	6.12	11.87	5.75

partitioning, the validation dataset has been considered statistically independent from the datasets used for training and testing purposes. Hence, the verification of ANN models through using the validation dataset can be considered a touchstone in

Table 3. Details of Suggested HDM-4 Pavement Deterioration Calibration Factors for Low Volume Roads in India.

Terrain Type	Total Cracking Progression	Raveling Progression	Rut Depth Progression	Roughness Progression
	K_{cpa}	K_{vp}	K_{rst}	K_{gp}
Plain	0.23	0.34	2.7	2.43
Rolling	0.23	0.27	2.17	2.17
Mountainous	0.23	0.54	1.5	2.17
Average for Study Area	0.227	0.381	2.122	2.3

(Source*:* Thube, 2006 [16])

Table 4. Details of Different ANN Model Architecture Types.

ANN Model Architecture Number	No. of Hidden Layers	No. of Neurons per Hidden Layer	Transfer Function Type
1	2	4	TenhAxon
2	2	4	SigmoidAxon
3	2	5	TenhAxon
4	2	5	SigmoidAxon
5	2	6	TenhAxon
6	2	6	SigmoidAxon
7	2	7	TenhAxon
8	2	7	SigmoidAxon
9	3	4	TenhAxon
10	3	4	SigmoidAxon
11	3	5	TenhAxon
12	3	5	SigmoidAxon
13	3	6	TenhAxon
14	3	6	SigmoidAxon
15	3	7	TenhAxon
16	3	7	SigmoidAxon

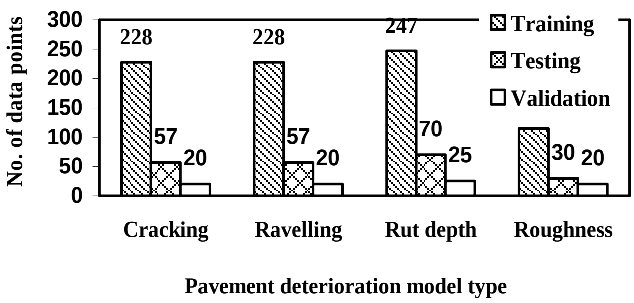

Fig. 2. Details of Datasets for ANN Model Development.

examining the performance of the developed ANN models from an implementation point of view. The details of the datasets selected for training, testing, and validation for ANN models in this study are given in Fig. 2.

Given the various ANN model architectures (Table 3), the weights of links among the neurons are determined through the training process. Designated transfer function types used for the training of ANN models and the Neurosolution-5 software have been used for analysis in this study. The training process involves presenting all example pattern pairs in the training dataset to the network and adjusting the weights of the connections according to the weight adjustment rules. The training process has been carried out for a fixed number of epochs (10,000).

After the training procedure is complete, the trained network is exposed to the testing dataset to check the efficacy of the training process. The testing datasets are fed into the trained ANN, and the testing error is calculated. If the testing error is within an acceptable level, the ANN model is considered reasonable. The model comparisons for attempted different ANN models are carried out by comparing the mean square error (MSE) values during testing stage. The details of MSE and goodness of fit (R2) variations for attempted different ANN models are shown in Figures 3 to 6. Finally, the ANN models corresponding to the minimum mean square error (MSE) and maximum goodness of fit (R^2) at the testing stage are selected. The details of the different model architectures for four ANN models are shown in Figs. 3 to 6.

Validation of ANN Models

After training and testing, the last and most critical step is to verify the model using a validation dataset. The details of selected datasets for the validation of different ANN models in this study are shown

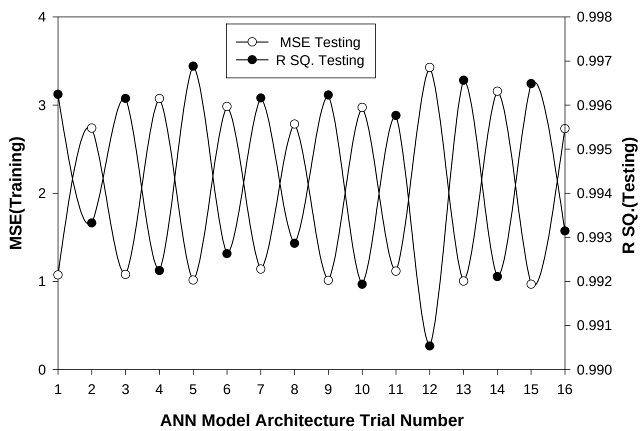

Fig. 3. Variation in MSE and R SQ. for the Cracking Progression ANN Model (Suggested Model Architecture No. 15)

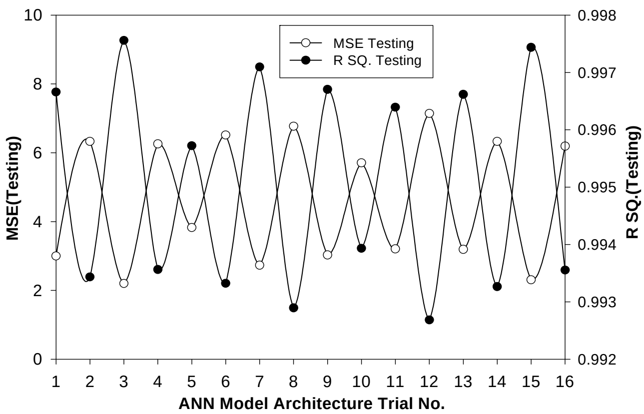

Fig. 4. Variation in MSE and R SQ. for the Raveling Progression ANN Model (Suggested Model Architecture No. 3)

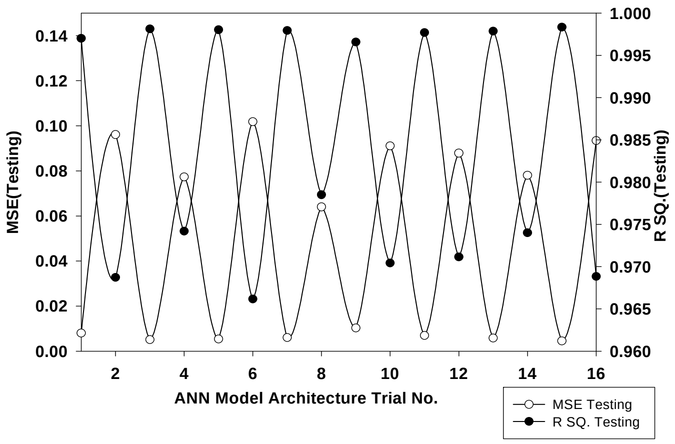

Fig. 5. Variation in MSE and R SQ. for the Roughness Progression ANN Model (Suggested Model Architecture No. 15)

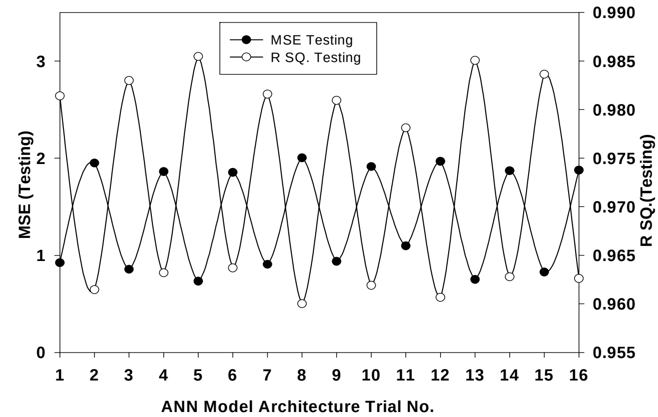

Fig. 6. Variation in MSE and R SQ. for the Rut-depth Progression ANN Model (Suggested Model Architecture No. 5)

in Fig. 2. Ten LVR sections (other than of model development) are chosen, and pavement performance data as per the requirements of

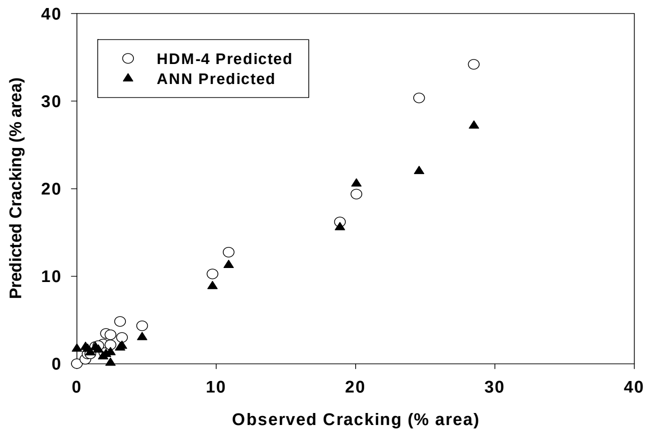

Fig. 7. Scatter Plot of Observed Distresses vs. HDM-4 and ANN Model Predicted Cracking.

ANN and HDM-4 models are collected for these roads. Similarly, the details of observed cracking, raveling, rut depth, and roughness for these roads are collected by carrying out the visual distress survey. Predictions of cracking, raveling, rut depth, and roughness are carried out by using the trained ANN models of selected architectures, as well as using the HDM-4 model calibration coefficient factors (Table 2). Scatter plots have been plotted between the observed distresses and the HDM-4 and ANN predicted distresses. These scatter plots for cracking, raveling, rut depth, and roughness distresses are given in Figs. 7 to 10, respectively. The linear relationship, goodness of fit (R^2), and root mean square error (RMSE) are calculated between the observed distresses and the HDM-4 and ANN predicted distresses, as shown in Table 5.

Conclusions

The following conclusions have been made based upon the study results:

1. Four unified ANN based models are suggested for the

Table 5. Details of Statistical Parameters between Observed vs. HDM-4 and ANN Predicted Distresses.

Serial No.	Model Description	Linear Relationship Details	R^2	RMSE
1	Cracking Progression Observed vs. HDM-4 Predict.	y = 1.1152x - 0.0768	0.971	1.737
	Cracking Progression Observed vs. ANN Predict.	y = 0.941x - 0.2981	0.977	1.364
2	Ravelling Progression Observed vs. HDM-4 Predict.	y = 1.1689x - 1.2155	0.971	4.068
	Ravelling Progression Observed vs. ANN Predict.	y = 0.927x + 0.2156	0.989	2.101
3	Rut depth Progression Observed vs. HDM-4 Predict.	y = 0.8187x +1.2184	0.914	0.661
	Rut depth Progression Observed vs. ANN Predict.	y = 0.9671x +0.1296	0.919	0.753
4	Roughness Progression Observed vs. HDM-4 Predict.	y =0.8131x + 1.2409	0.852	0.183
	Roughness Progression Observed vs. ANN Predict.	y = 1.0541x – 0.4209	0.969	0.094

prediction of cracking, raveling, rut depth, and roughness progression for LVR in India.

2. The suggested unified ANN models are more useful than HDM-4 models for distress predictions since the unified ANN models is applicable to all types of terrains. The HDM-4 model requires separate local calibrations for plain, rolling and mountainous terrain types.
3. Different ANN model architectures were examined by carrying out various trials. Through varying the number of hidden layers and the number of neurons in each hidden layer, the model architecture corresponding to the minimum mean square error (MSE) at the testing stage has been suggested for each distress type.
4. The suggested ANN models show a high goodness of fit (R^2 value) between observed distresses and ANN predicted distresses of more than a ratio of 0.98 for cracking, raveling, rut depth, and roughness progression models at the testing stage. This shows an efficacy of the suggested ANN models.
5. The suggested ANN models show a high goodness of fit (R^2 value) between observed distresses and ANN predicted distresses of more than a ratio of 0.97 for cracking, raveling, and roughness progression models and more than a ratio of 0.92 for rut depth progression models at the validation stage. This demonstrates an efficacy of the suggested ANN models.
6. The ANN models show a higher goodness of fit regarding the predictability of distresses than that of HDM-4 calibrated distresses. This is true for all four different ANN models, proving the success of ANN models over HMD-4 pavement deterioration models in predicting distresses.
7. The suggested ANN models will be useful in the accurate prediction of cracking, raveling, rut depth, and roughness. The models can calculate the appropriate time for various maintenance strategies to preserve the huge network of LVR in India and other developing countries with similar environmental and traffic conditions.

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