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Artificial Neural Network Based Development of Pavement Depreciation Models for Urban Roads

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ABSTRACT

A productive road transportation framework is of fundamental significance to economy of any country. Road transport in India, involves a predominant position in the general transportation arrangement of the nation because of its favourable circumstances as far as simple accessibility, adaptability of operation and reliability. The importance of preserving an adequate condition of the road network is widely recognized. Although, creating and keeping up a valuable road structure is not a simple assignment. It requires careful arranging, gigantic assets, challenging construction technique and other related perspectives. Pavement Depreciation models, which simulate the depreciation procedure of pavement conditions and give pavement conditions forecasting over time, plays a vital part in Pavement Management System (PMS). The main objective of this study is to develop pavement performance models by applying neural network algorithm for urban road network in India.

Key words: Pavement Management System, Pavement Performance Models, Cost, Safety

INTRODUCTION

Road transport has been acknowledged as the primary requirement for the development of basic infrastructure such as agriculture, industries and power sector etc. leading to overall economic growth of the country. It is essential for a highway engineer to attempt establishing an acceptable pavement condition level from economic, safety and environmental point of view. To accomplish this, a highway engineer must be equipped with tools and techniques for the prediction of the functional and structural condition of pavement, as built and after providing different types of maintenance measures or rehabilitation treatments.

In current economic condition of obliged spending plans, as the current road framework has matured, a more methodical approach towards deciding upkeep and restoration needs is required. Pavement condition execution models, which simulate the depreciation procedure of pavement conditions and give pavement conditions forecasting over time, plays a pivotal role in pavement management system (PMS). A new approach, which can be categorized as "biologically-inspired", is taking the territory from its traditional counterpart. Typical models in this category are neural networks and genetic algorithms. Neural network abstracts the underlying relationship between dependent and independent variables from the exemplar data pairs and express it as forms of weight matrix.

RESEARCH SURVEY

In spite of the fact that pavement execution models may take diverse structures, ordinarily, they relate the indicators of pavement conditions, for example, cracking index, roughness, or rutting, to explanatory variables such as traffic loads, environmental factors, age, and pavement structure. The motivation behind a model is to set up a causal connection between the pavement condition and these elements that is considered affecting execution of pavements. Three general classifications of pavement performance models exist presently. These are deterministic models, probabilistic models, and biologically-inspired models.

Deterministic Models

For deterministic models, the functional frame is thought to be expressly indicated. Deterministic models can be additionally partitioned into three subcategories, which are pure empirical models, mechanistic-empirical models, and expert system models.

Probabilistic Models

Inherent variability of material properties, environmental conditions, traffic characteristics, and the subjective nature of condition studies make the pavement execution acquire attributes of a stochastic procedure. A well-known probabilistic pavement execution model is the Markov chain model, which make use of Markovian method in pavement execution demonstrating. The essential Markov model demonstrate comprises of introductory stage probability and the transition matrix as appeared in Equation 1 [4].

$$P_i = P_0(P)^i \tag{1}$$

where Po - initial state probability, Pi - state probability of i^{th} duty cycle, P- probability transition matrix, and i - duty cycle.

Biologically-inspired Models

Common models in this classification are genetic algorithm (GA) and artificial neural network (ANN) models. A genetic algorithm gets its idea from the procedure of development in nature. A current utilization of genetic algorithm in the pavement execution modelling i in which a roughness performance model is produced by utilizing the genetic programming calculation. In the wake of running around 50 eras, the best model was at last acquired, which is communicated in Equation 2 as [1]:

$$R_t = R_{t-1} + \log_{10}(R_{t-1} + SN) \tag{2}$$

where, R_t = pavement roughness at age t, R_{t-1} = pavement roughness at age t-1, and SN = structural number modified for subgrade strength.

Another biologically-inspired is artificial neural network (ANN). ANN framework can be viewed as the exceptionally disentangled models of the human cerebrum framework. Numerous utilizations of ANN to pavement performance modelling have been endeavored delivering rousing outcomes.

STUDY METHODOLOGY

Four unified ANN models has been developed in this study to forecast the total cracking area (% area), total raveling area (% area), rut depth (in mm), and total roughness progression (in IRI) for urban road and the popular ANN training algorithm of standard 'Back-Propagation (BP)' algorithm is employed for neural network training. Following sections describes the techniques in modeling pavement performance over time:

Techniques Applied in Pavement Performance Modeling

There are two particular sorts of models accessible for pavement condition forecasting.

Static Model

The development of such models depends on statistical analysis. As a result, formats of these models generally lack in accuracy and complicated due to the multitude of variables associated.

Dynamic Model

This kind of model depends on chronicled execution of pavement attributes, independent of different factors utilized as a part of the static model. By understanding the elements of the changing procedure after some time, this kind of model can estimate future conditions in view of the past conditions. If external and basic conditions are not fundamentally changed, the model in view of recorded data could create a sensibly precise figure of future pavement condition. This kind of model is called time-series model, which has been effectively connected in transportation designing.

Artificial Neural Networks

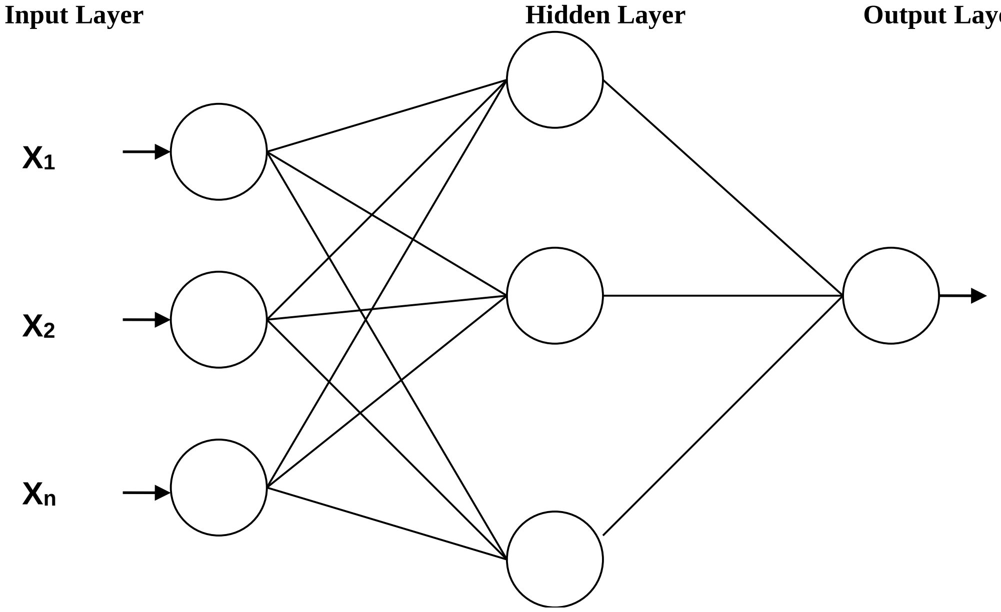
An Artificial Neural Network is a parallel information-processing framework that has various execution attributes like biological neural systems. A neural net comprises of countless preparing components called neurons. Every neuron is associated with different neurons by methods of directed links and each directed link has a weight related with it. With a specific end goal to develop a neural system for taking care of a specific issue, three parts should be resolved to start with, including architecture, learning method, and neuron activation function. As an illustration, a typical three-layered neural network with one output neuron is shown in the Fig. 1.

Back Propagation Method

Back-Propagation (BP) is an effective training method for multiplayer neural networks. Its appearance has played a major role in the re-emergence of neural networks as tools for solving a wide variety of problems especially after the downturn of neural networks due to limitations of single-layer neural networks. BP is simply the implementation of the gradient descend method to minimize the total squared error of the output computed by the network.

ANN Model Implementation

There are two forms of implementation, hardware and software. The hardware implementation involves neuron realization by using VLSI, optic, or molecular technologies. Software implementation involves software simulation and algorithm-based applications. Present study falls in the latter category of algorithm-based application, which actually applies the neural network algorithm as a means to model the vague mechanism underlying the pavement deterioration process over time.



Note: X_1, X_2,…X_n – Input to the Neural Network ; Y- Output of Neural Network

Fig. 1 Three layered neuron network

ANN MODELS DEVELOPMENT

The study involves development of four artificial neural network models to determine the total cracking (% area), raveling (% area), rut conditions (in mm) and roughness (in IRI) for flexible pavement sections. The back propagation algorithm is most widely used in this study for neural network training.

Data collection and Data Processing

Road inventory details in addition to six cycles of pavement execution information (during pre-monsoon, post-monsoon and winter season) has been collected. It includes various pavement distresses, sub grade characterization and traffic data that have been collected from 61 selected in service rural road pavement sections in year 2014, 2015 and 2016 and time series pavement execution database are created from it. This database has been accordingly utilized for the advancement of four individual ANN models.

Identification of Variables

From the analysis, it is apparent that the pavement's advancement generally relies on upon four worldwide factors as: traffic, pavement age, dominant climatic conditions, and structural capacity. These factors characterize the start and additionally the progression of the distress [2] [5-6]. The class of information and variables used to create the ANN models are chosen principally on the premise of pavement depreciation models in HDM-4 and subtle elements for every individual ANN models in this study are given in Tables 1 and 2.

Formation of Datasets

The target of this progression is to prepare three datasets in an arrangement that can be momentarily utilized for network training, testing, and validation. The details of training, testing and validation datasets for four ANN models proposed in the present review are given in Fig. 2.

Table -1 ANN Models Input Variables [3]

S. No.	Input Variables	ANN Model			
		Cracking Progression Model	Ravelling Progression Model	Rut Depth Progression Model	Roughness Progression Model
1.	Age (months)	✓	✓	✓	✓
2.	Initial cracking area (% area)	✓			
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 (Motorised)	✓	✓	✓	✓
12.	AADT (Non-motorised)	✓	✓	✓	✓
13.	Percentage of Truck volume	✓	✓	✓	✓
14.	Composition of Commercial vehicles (%)	✓	✓	✓	✓
15.	Percentage duration of dry season	✓	✓	✓	✓
16.	Mean monthly precipitation (mm)	✓	✓	✓	✓
17.	Mean 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 (kmph)	✓	✓	✓	✓
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 Ravelling area (% area) at start of analysis cycle		✓		
28.	Observed Cracking area (%) during present cycle			✓	✓
29.	Observed Ravelling 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 ANN Models Output Variables

S. No.	ANN Model	Output Variables
1	Cracking progression model	Total cracking area (% area)
2	Ravelling progression model	Total ravelling area (% area)
3	Rut depth progression model	Total rut depth progression (in mm)
4	Roughness progression model	Total roughness progression (in IRI)

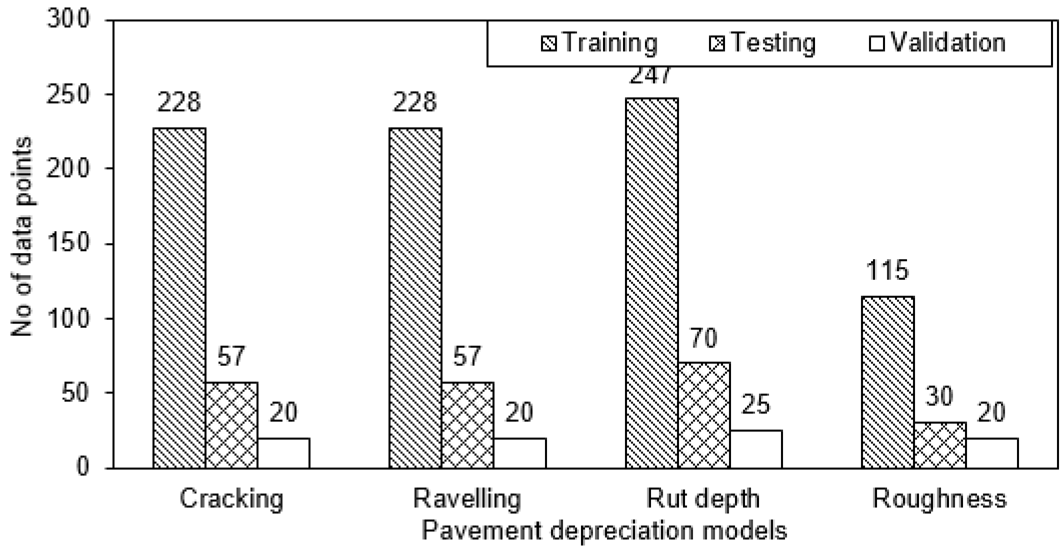


Fig. 2 ANN model development datasets

MODEL FRAMEWORK DESIGN

Four ANN Models i.e. cracking progression, raveling progression, rut depth progression, and roughness progression models has been developed in this study and following procedure is followed for developing models.

Model Architecture

In current study, all input and output variables as described in Table 1 and 2 are kept constant and variation are carried out in number of hidden layers and neurons. Twelve ANN model architectures comprising of variations in number of hidden layers and number of neurons per hidden layers have been attempted for each cracking, raveling, rut depth, and roughness progression models and the details of same are given in Fig. 3.

Training and Testing Set Generation

Given the different ANN models as portrayed in Fig. 4, the weights of connections among the neurons are settled through the training procedure. In this review, training procedure is completed for fixed number of epoch of 10,000. After completion, the testing datasets are sustained into the prepared ANN and the testing error is figured out. The model examinations for different endeavored ANN designs for cracking, raveling, rut depth and roughness progression models are completed by looking at root mean square error (RMSE) during the training and testing stage and the details of RMSE variations with various model structures are appeared in Fig. 4 to Fig. 7. Typical training details of model architecture no. 8 for raveling progression ANN model are shown in Fig. 8.

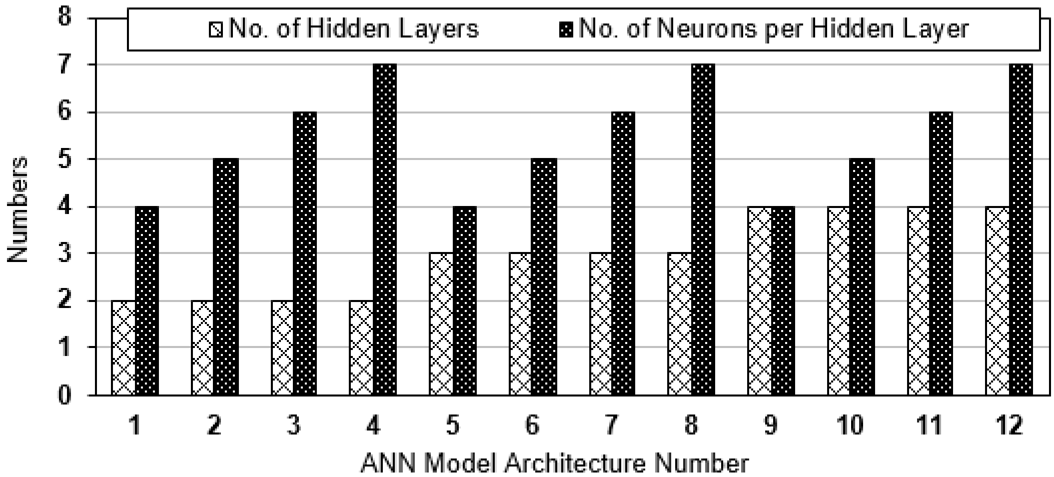


Fig. 3 Details of different ANN model architectures

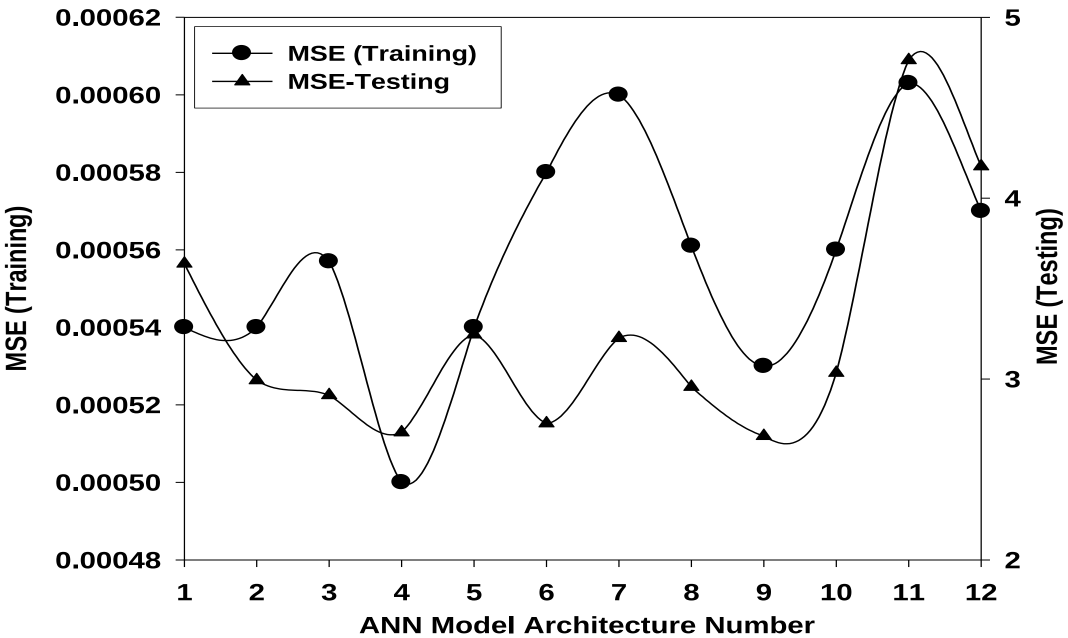


Fig. 4 Details of ANN architecture trials for cracking progression distress model **(suggested ANN model architecture no. 4)**

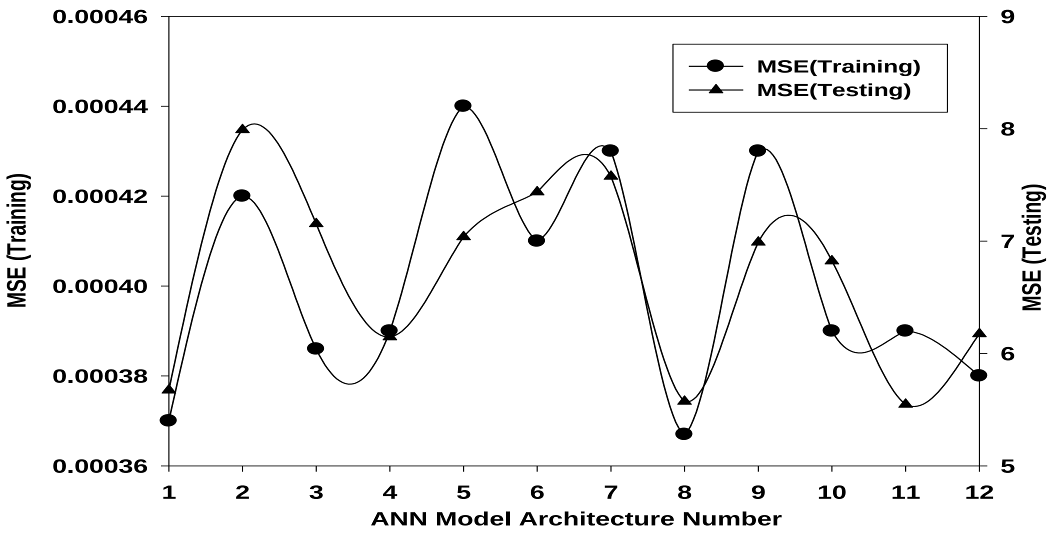


Fig. 5 Details of ANN architecture trials for raveling progression distress model (suggested ann model architecture no.8)

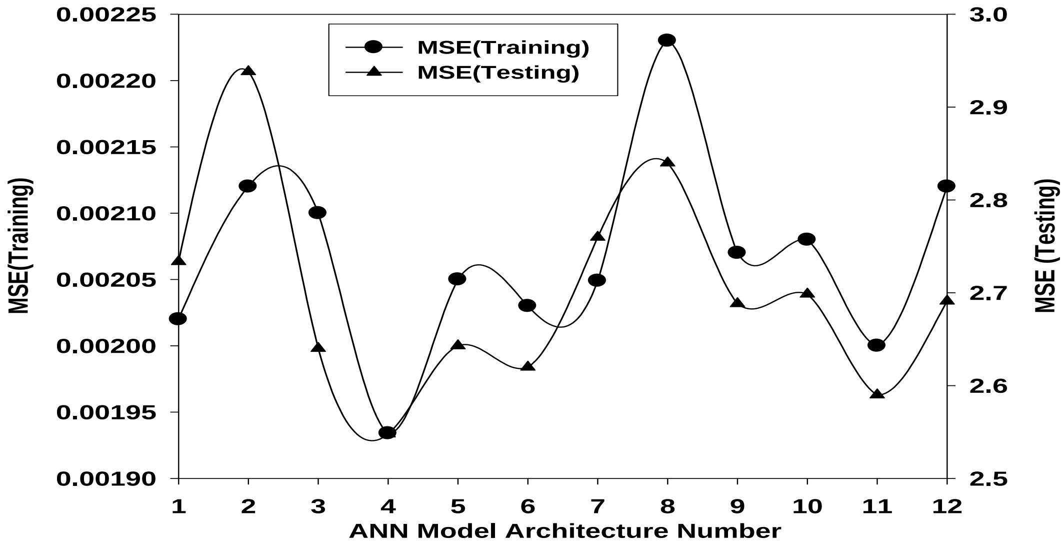


Fig. 6 Details of ANN architecture trials for rut depth progression distress model (suggested ANN model architecture no.4)

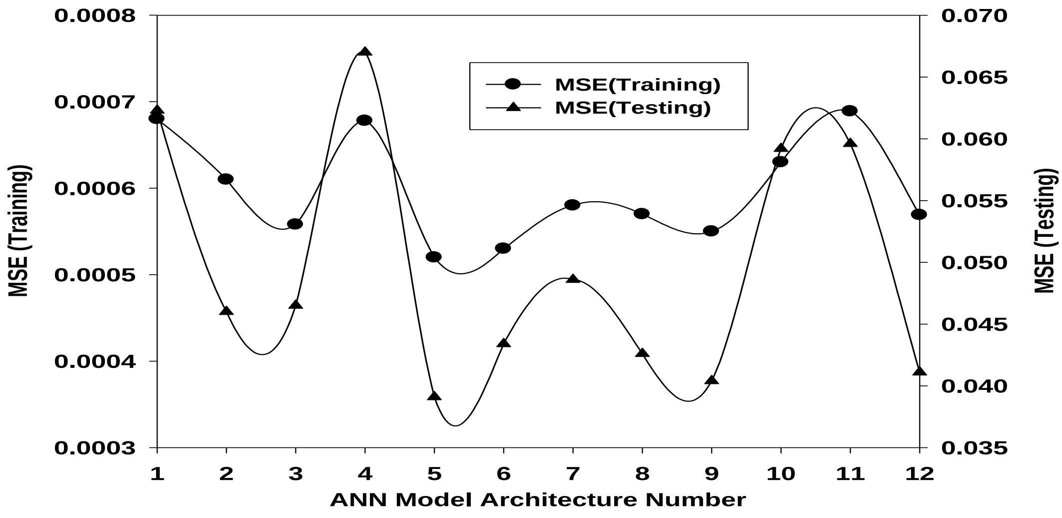
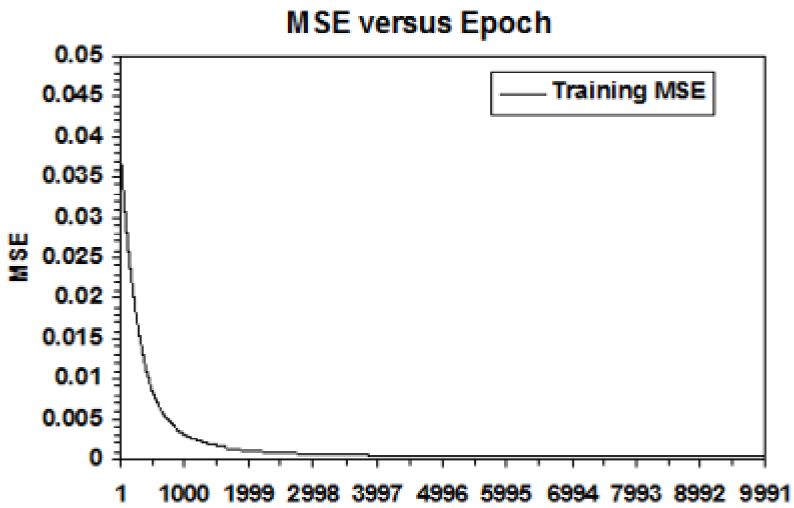


Fig. 7 Details of ANN architecture trials for roughness progression distress model (suggested ANN model architecture no.5)

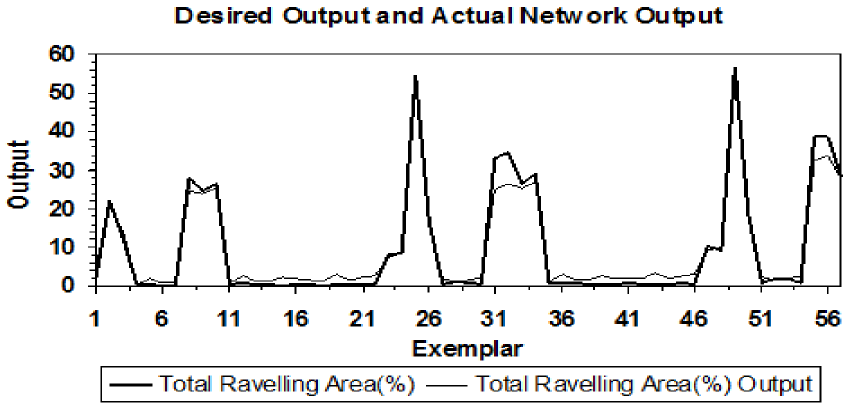


Best Network	*Training*
Epoch	10000
Minimum MSE	0.000369882
Final MSE	0.000369882

Fig. 8 Typical training details of model architecture no. 8 for raveling progression ANN model

ANN MODELS VALIDATION

Subsequent to training and testing, the last and furthermore the most basic step is to check the model utilizing using a validation dataset. The details of number of validation data points for different ANN models in the present study are shown in Fig. 3. Typical validation details of ANN model architecture no.8 for ravelling progression ANN Model is shown in Fig. 9. Scatter plots are plotted between observed distresses vs. HDM-4 and ANN predicted distress and the details of scatter plots for cracking, ravelling, rut depth and roughness distresses are shown in Fig. 10 to Fig.13.



Performance	Total Ravelling Area (%)
MSE	5.593410393
NMSE	0.025861191
MAE	1.6845602
Min Abs Error	0.125505504
Max Abs Error	8.148419354
r	0.991984982

Fig. 9 Typical validation details of ANN model architecture no.8 for ravelling progression ANN model

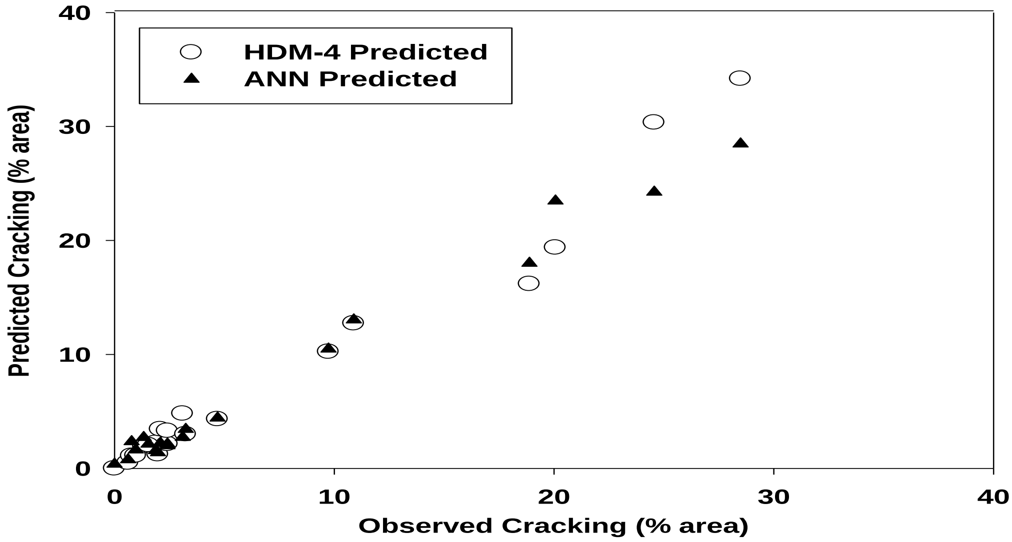


Fig. 10 Observed vs. HDM-4 and ANN model predicted cracking

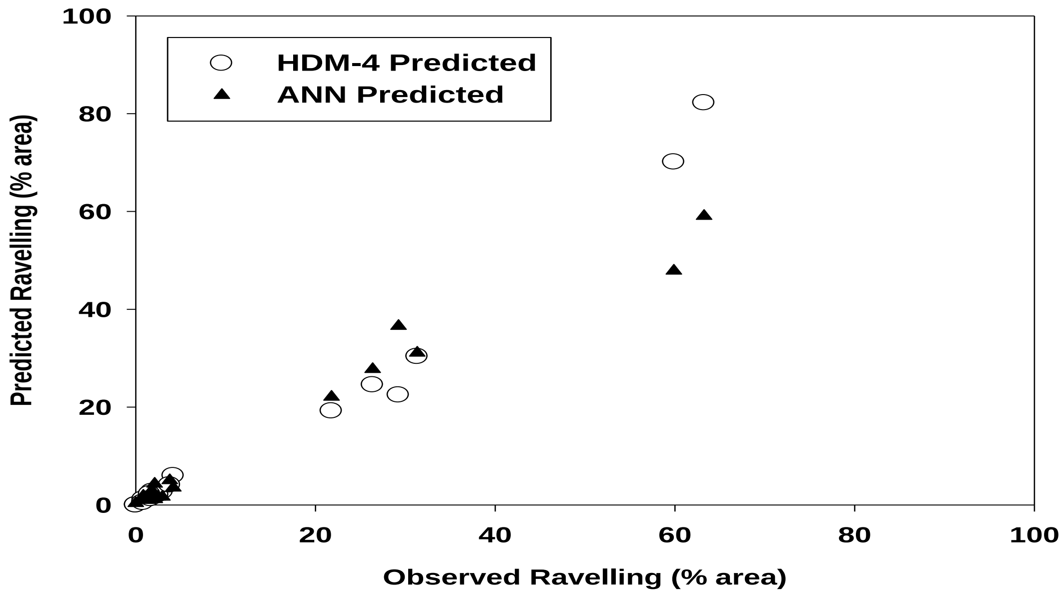


Fig. 11 Observed vs. HDM-4 and ANN model predicted ravelling

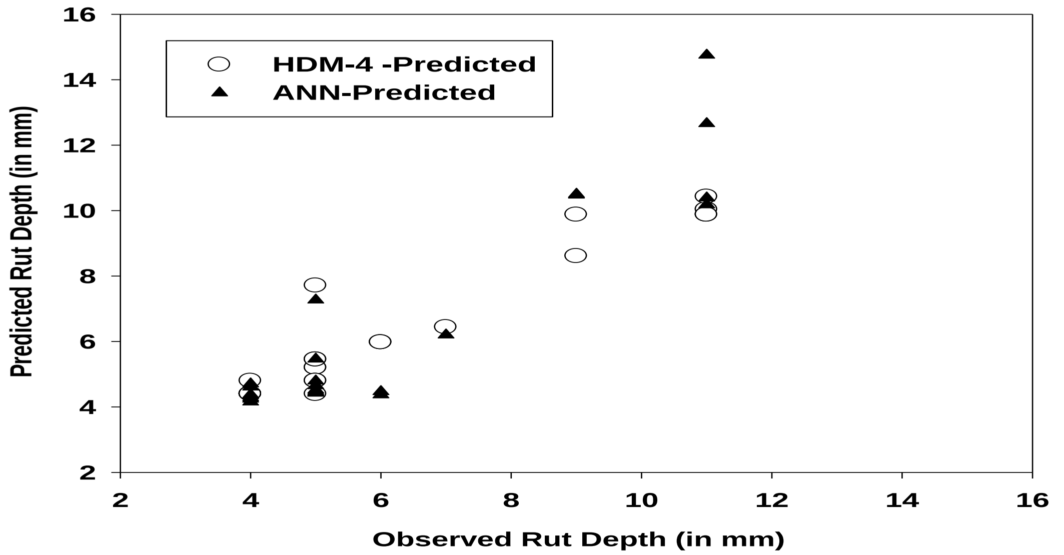


Fig. 12 Observed vs. HDM-4 and ANN model predicted rut depth

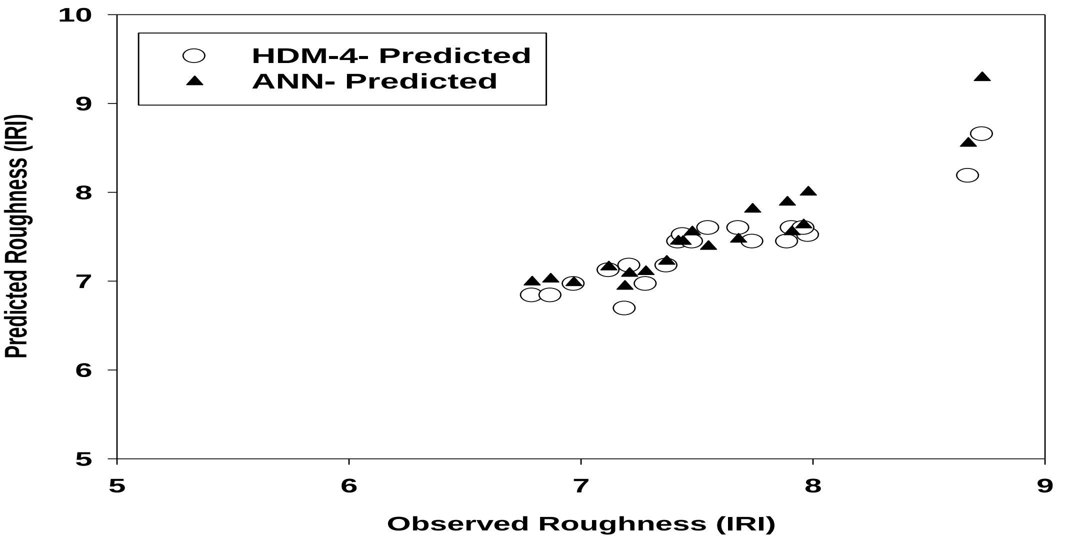


Fig. 13 Observed vs. HDM-4 and ANN model predicted roughness progression

Table -3 Statistical Parameters Between Observed vs. HDM-4 and ANN Model Predicted Distresses

S. No.	Model Description	Linear relationship details	R^2	RMSE
1	Cracking progression observed vs. HDM-4 predict.	y = 1.1152x - 0.0968	0.99	1.93
	Cracking progression observed vs. ANN predict.	y = 1.0129x +0.3009	0.98	1.06
2	Ravelling progression observed vs. HDM-4 predict.	y = 1.1689x - 1.2155	0.99	4.06
	Ravelling progression observed vs. ANN predict.	y = 0.9095x + 0.9814	0.99	3.05
3	Rut depth progression observed vs. HDM-4 predict.	y = 0.8189x +1.2184	0.89	0.85
	Rut depth progression observed vs. ANN predict.	y = 0.9389x +0.2424	0.89	0.86
4	Roughness progression observed vs. HDM-4 predict.	y =0.8131x + 1.2409	0.85	0.18
	Roughness progression observed vs. ANN predict.	y = 1.0351x – 0.3013	0.89	0.21

CONCLUSIONS

Four individual unified ANN based distress prediction models for prediction of total cracking, ravelling, rut depth and roughness progression are developed by using the pavement performance data, as collected in the year 2014,2015, and 2016 during the study. The input parameters for each of the four models have been decided on the basis of HDM-4 models, and the database is divided in two parts as - training and testing. Twelve different architectures of ANN models have been attempted for each of the four models. Suggested ANN models have also been validated for the pavement distress data collected during latest cycle, by comparing observed distresses vs. ANN predicted distresses. The goodness of fit (R^2) between ANN predicted vs. observed distresses show values more than 0.89 for all four ANN models, and hence shows the efficiency of suggested ANN models. The performance of suggested ANN models has also been compared with the predictions made by calibrated HDM-4 models for all three terrains, and the suggested ANN model shows the better performance in cracking, ravelling, edge-break and roughness prediction models as compared with the performance of calibrated HDM-4 models.

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