Artificial Neural Network-Based Distress Prediction Model: A Case of ERA Asphalt Concrete Pavements

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Abstract

In pavement management, predicting the amount of distress of pavement plays a substantial role to determine the overall level of performance of a pavement. In current practice, even though the Federal Government of Ethiopia is investing large amounts of money on road construction projects every year, poor & untimely maintenance and rehabilitation is leading to the deterioration of pavement performance. The aim of this research is to develop artificial neural network (ANN-based) models in order to predict pavement distresses as a decision making tool for planning, budgeting, prioritizing and optimizing maintenance and rehabilitation strategies throughout a pavement service time. The study collected asphalt concrete pavement distresses such as cracking, rutting, raveling, pothole and age break from ERA Road Asset Management Department covering about 179 case study projects spread across the nation's road network. Goodness of Fit (R^2) and Root Mean Square Error (RMSE) were used to evaluate the developed models. The trained models (85%) have been validated using validating dataset (15%). R^2 between ANN predicted vs. observed distresses to both training and validating dataset showed a value of 0.84 to 0.97 for the developed ANN distress prediction models. The results identified significant independent variables or factors affecting asphalt concrete pavement distresses. Average Annual Daily Freight Vehicles (AADFV), Adjusted Structural Number (SNP), Drainage Condition (DC), Annual Rain Fall (ARF), Average Annual Traffic (AADT) and Service Life (SL) were significant factors affecting rutting, while Service Life (SL) Minimum temperature (MinT), Average Annual Daily Traffic (AADT), AADFV and ARF were identified as critical factors affecting raveling. In addition, SNP, AADT, Equivalent Single Axel load (ESAL) and AADFV are contributing factors for potholes, while Deflection (Def), DC, AADFV, ESAL, SNP and maximum temperature (MaxT) are the root causes for cracking. Furthermore, ESAL, SNP, ARF, Def and AADFV are critical factors affecting edge break distress. The developed models can serve as a useful tool in the decision-making process for maintaining road assets.

Keywords: Asphalt Concrete Pavement, Pavement Management System, Distresses, Artificial Neural Network, Multilayer Perceptron, Prediction Model

1 Introduction

Road Asset is one of the primary requirements for the development of basic infrastructure to various sectors including agriculture, manufacturing and power sector leading to overall economic growth of a nation. Ethiopia has 126,773 km road network in 2018 (ERA, 2018). Effective road asset management plays a significant role in managing the condition of road networks efficiently based oncost-effective strategies and/or treatments applied at a given time to preserve the required level of service through-out its lifecycle (Alharbi, 2018). In other words, timely maintenance and repair keeps road assets in good condition, ensures safety, avoids extra costs & reduces inconvenience to the public. Thus, a road asset management must utilize matured & systematic tools, methods and techniques in capturing and assessing as-built functional and structural condition of a road/ pavement to help in planning, budgeting, prioritizing and optimizing new construction solutions or applying different types of maintenance treatments and/or rehabilitation measures. In current practice, different studies have developed various pavement performance models to meet road asset management goals. Although these models may take diverse forms, three major categories of pavement performance models prevail worldwide in developing causal correlation between pavement condition & factors that influence the performance of pavement over time. These are deterministic, probabilistic, and biologically-inspired models (Jain, 2017a). Deterministic model forecast a single dependent value (e.g., pavement condition index, PCI) from one or more independent variables (e.g., pavement age, traffic loading, environment and structural parameters). Deterministic models commonly use empirical, empirical-mechanistic or expert system using regression models. The deterministic model assumes that a pavement behavior follows a predetermined pattern that can be formulated by a specific equation relating the pavement performance indicator to one or more explanatory variables. However, this approach may oversimplify the pavement deterioration process since the uncertainty observed in pavement deterioration is not accounted for.

An alternative approach is s probabilistic model such as Markov chain, which treats pavement condition as a random variable and is capable of considering the uncertainty associated with pavement deterioration. In this approach, a set of transition probabilities are estimated depending on the quantity of available pavement condition survey data. However, due to the scarcity of data, expert knowledge is usually consulted to obtain the stationary transition probability matrix. Considering the subjective nature of pavement expert knowledge and the variety of pavement deterioration patterns

across the associated variables, stationary transition probability matrix is questioned for appropriateness.

With deeper understanding of biological phenomena, such as functioning of human brain and evolution of nature, a new breed of modeling methodology has begun to thrive, which are called "biologicallyinspired" models.

"Biologically-inspired" models focus on designs and developments of computer algorithms and models based on inspirations from biology. This includes genetic algorithms, ant-swarm optimization and artificial neural network (ANN). For example, artificial neural network (ANN) abstracts the causal relationship between dependent and independent variables from a dataset and express it as forms of weight matrix using the connections of a biological neuron modeled as weights between the variables (Jain, 2017a). ANN is recognized for acquiring the knowledge hidden in historical data for information-processing and computation purposes without assuming the relationships between variables and because of the self-learning, self-organizing functions, and high-speed computing capabilities (Lesniak and Juszczyk, 2018a; Patel and Jha, 2015a).

Neural networks have been applied in different fields including civil engineering and construction management such as cost estimation, safety prediction, structural design and performance evaluation to list a few. Thus, the objective of this study is to develop ANN distresses prediction models for asphalt concrete pavement in in determining the relative importance of various input variables on the deterioration of pavement conditions.

2 Literature Review

A systemic literature review was conducted using content analysis to capture and analyse models developed relating to performance prediction of flexible pavements. Table 1 summarizes the findings. Based on the findings, service life, climate (temperature & rainfall), traffic related factor (AADT, AADCV and ESAL) and pavement layers strength (MSN) are common input variables used in predicting performance and distresses of flexible pavement. In addition, ANN is identified as the most widely used method for pavement performance modelling.

Authors and Year	Dependent Variables	Independent Variables	Study Area	Modelling Technique	R^2 & Error
AASHO (1962)	Present Serviceability Index	Slope variance, Area cracking and patching, Rutting	Different country	Statistical Regression	Sample = 74 R2 = 0.844; S.E. = 0.38
Hodges, Rolt & Jones (1975); Parsley and Robinson (1982)	Roughness	Traffic load and pavements strength	Kenya		
	Area Of Cracking Plus Patching	Traffic load and pavements strength			
Queiroz (1981)	Roughness Progression	Pavements strength	Brazil		Sample = 73 ; R^2 = 0.53; S.E. = 10.2 counts/km
	Cracking Initiation	Age, Traffic load and pavements strength			Sample = 76; R^2 = 0.35; S.E. = 17.1
	Cracking Progression	Age, Traffic load and pavements strength			Sample = 76; R^2 = 0.64; S.E. = 12.6
Sood (1996)	Cracking Initiation	Cumulative standard axle load and pavements strength	India	Statistical Regression	Sample = 20; R^2 = 0.45; S.E. = 0.43
	Cracking Progression	Traffic load, Initial cracking and pavements strength			Sample = 124; R^2 = 0.25; S.E. = 1.14
	Raveling	Traffic loading and construction quality			26; R^2 = 0.43; S.E. = 0.38
	Pothole Initiation	Thickness of bituminous layer, No. of vehicles axles per year			Sample = 12; R^2 = 0.75; S.E. = 0.27

Owusu-Ababio (1998)	Pavement Distress Index (PDI)	pavement surface thickness, pavement age, traffic level (ESAL/day), base thickness, and road bed condition	US, Wisconsin		
Lou, Gunaratne, Lu, & Dietrich (2001)	Crack Condition	CI(t-2), CI(t-1); surface type, age and maintenance cycle	US, Florida	ANN	R^2 = 0.91; S.E. = 0.06
				AR	R^2 = 0.65; S.E. = 0.12
Terzi (2005)	PSI	Slope variance, Area cracking, patching and Rutting	US, Florida	ANN	Sample 148; R^2 = 0.99
Makendran (2015)	Roughness	CVPD, Age and MSN	India	ANN	Sample = 120; R^2 = 0.896; RMSE = 0.77
	Cracking				Sample = 120; R^2 = 0.916; RMSE = 1.56
	Pothole				Sample = 120, R^2 = 0.878; RMSE = 2.42
Jain (2017)	Cracking Progression Model (% Area)	Temperature, rainfall, age, % Truck volume, AADT, subgrade shear strength, SNP, previous cracking	India	ANN	R^2= 0.98 , RMSE= 1.06
	Raveling Progression Model (% Area)	Temperature, rainfall, age, % Truck volume, AADT, subgrade shear strength, SNP, previous cracking and raveling			R^2= 0.99, RMSE 3.05
	Rut Depth Progression Model (mm)	Temperature, rainfall, age, % Truck volume, AADT, subgrade shear strength, SNP and previous cracking, raveling and rut depth			R^2= 0.89, RMSE = 0.86
Alharbi, (2018)	Rutting Index	Temperature, age and previous Rut	US, Iowa	ANN	R^2= 0.7, RMSE = 9.67

	Riding Index	Temperature, age , thickness, previous IRI and Subgrade stiffness			R^2=0.91, RMSE = 8.69
	Cracking Index	Temperature, age , Previous crack and SN			R^2=0.78, RMSE = 14.68
	Rutting Index	Temperature, age and previous Rut		MLR	R^2= 0.41, RMSE = 12.1
	Riding Index	Temperature, age , thickness, previous IRI and Subgrade stiffness			R^2=0.57, RMSE = 12.97

Table 1 Summary of Performance Prediction Models for Flexible Pavements

3 Current Practice

According to ERA's Annual Book of Road & Bridge Data, Ethiopia has approximately 155,830 km of road network including woreda & municipality roads (ERA, 2022). From this, 18.3% are federal roads administered by Ethiopian Road Administration (ERA) and of this percentage 16,377km (57.25%) is asphalt and 12,231km (42.75%) is gravel, while the remaining roads are administered by Regional Road Authorities. Figure 1 illustrates the progress of asphalt road network through the last three decades.

Currently, ERA has a Road Asset System Management Directorate (RASMD) to manage roads by collecting condition and traffic data; conducting analysis & proposing interventions based on the output to advise ERA's top management for decision making on nationwide as an asset management strategy (ERA, 2022). ERA has also established a Pavement Management System (PMS) that incorporates road condition data collection equipment and software to systematically manage road networks.

Typically, ERA conducts road conditions survey every other year by outsourcing to consulting engineers, while traffic count and axle load weight are collected by inhouse team three times per year. However, the condition survey, estimation of the amount of distress and extent of damage of road pavement is conducted using professional or expert judgment based on past experience of field engineers & though visual condition survey, which is very subjective. The collected distresses is then rated using a rating scale of ERA-PMS (0100 scale) and finally a pavement status is rated as very good, good, fair, poor and very poor, which is time taking, costly and more distress can happen before finishing a condition survey. In addition, the automatic road condition (distresses) data collection equipment, called Hawkeye 1000 has not been working since 2012.

Through the years, ERA has also been testing various road asset management systems and software programs. However, ERA does not have a systematic road management system yet, but it's working towards implementing its own integrated Road Asset Management System (RAMS). Thus, this study will develop ANN models to encompass the effect of local conditions, which can be an input towards ERA's effort.

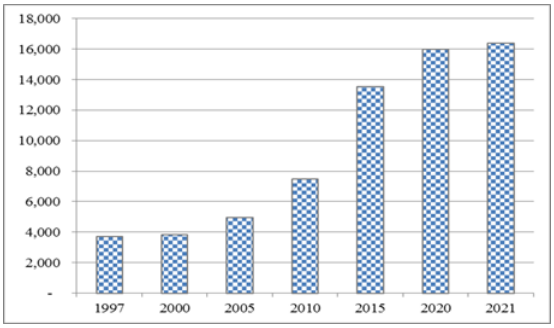


Figure 1 Asphalt Road Progress in Federal Road Network (ERA, 2022)

4 Study Methodology

The entire research work has been divided into four steps:

1. Conduct literature review to capture common distresses;
2. Collect objective data (road condition survey along with potential factors) from ERA;
3. Clean data and develop five (5) pavement distresses prediction model using ANN Multilayer Perceptron through WEKA Tools (Version 3.9.5 and;
4. Conduct validation analysis for developed models. It is important to note that 85% of the data is used for training purposes, while 15% of the data is used for validation purposes. A Goodness of Fit (R2) and Root Mean Square Error (RMSE) were used to evaluate the developed models. The research methodology is described using a flow chart (Figure 2).

5 Population & Sampling Method

In this study the population is considered as ERA's asphalt concrete (AC) pavement projects completed between 2003 and 2016 G.C. This is due to the fact that in these years the design standard manual & specification used during design & construction are similar and a network level comprehensive and well organized condition surveys were conducted during this period.

This study adopts Cochran (1977a) developed formula shown in Equation 1 to calculate the minimum representative sample size for unknown population based on three parameters: estimated proportion of an attribute that is present in the population ranges between 0 and 1; Z-value of desired confidence level and; precision level.

$$n = (Z)^2 \times P\,(1\text{-}P) / (E)^2 \qquad (1)$$

Where n is the required sample size for unknown population, Z is z-value or score of required confidence level and P is the proportion of population.

The z-score for 90%. 95% and 99% confidence interval are 1.645, 1.96 and 2.326. In this study, 50% critical value of P, ±10% acceptable margin of error and 90% confidence level were used to determine the minimum representative sample size. Based on this, the minimum required sample size of this study was calculated as 68.

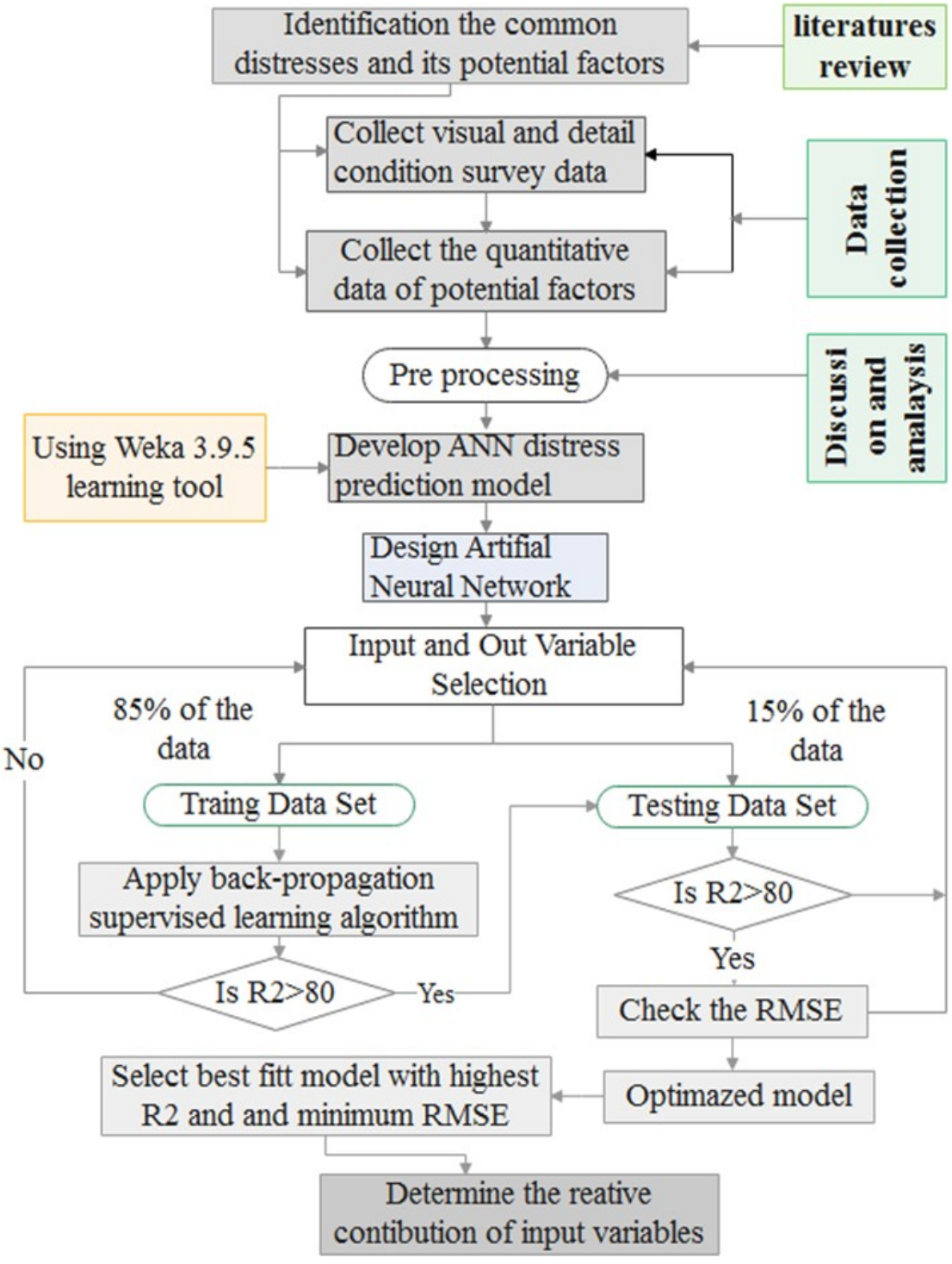


Figure 2 Research Methodology Flow Chart

Thus, for this study, 179 in service AC pavement projects have been collected from ERA. However, 20.67% of the projects are eliminated as it has more than 50% missing values, while 8.94% of the projects are eliminated as outlier's and extreme values with the help of interquartile ranges (IQR) using WEKA filter tool. As a result, the total sample size used for modeling is 126 (with 107 projects used for training and 19 projects used for validation purposes), which is above minimum requirement.

6 Pavement Distresses Prediction Model Development

In developing a realistic & close-to-actual pavement performance prediction models requires identifying robust performance prediction approaches. In this study, ANN Multilayer Perceptron has been used to predict pavement distresses. As discussed above, factors that affect flexible pavements are multiple and complex and ANN is suitable to solve and identify a clear relationship with distresses.

According to Kriesel (2005) and Chauhan (2019a), optimum ANN models depend on three fundamental components of neural network: ANN Architecture, Learning Algorithm and Transfer Function and these are discussed briefly in the following sections.

6.1 ANN Architecture

In this study, multilayer feed forward neural network architecture is used as it is suitable for multiple variables that have simultaneous impact. Typically, the network consists of a minimum of three layers: input, hidden and output layer. All input (independent) & output (dependent) variable are kept constant and change in number of hidden layers and neurons were carried out.

Twelve ANN model architectures containing of change in number of hidden layers and number of neurons per hidden layers are trained for Rut depth, Raveling, Pothole, Cracking and Edge Break models. The typical details of ANN model architecture of rutting and raveling are described in Figure 3 as an example.

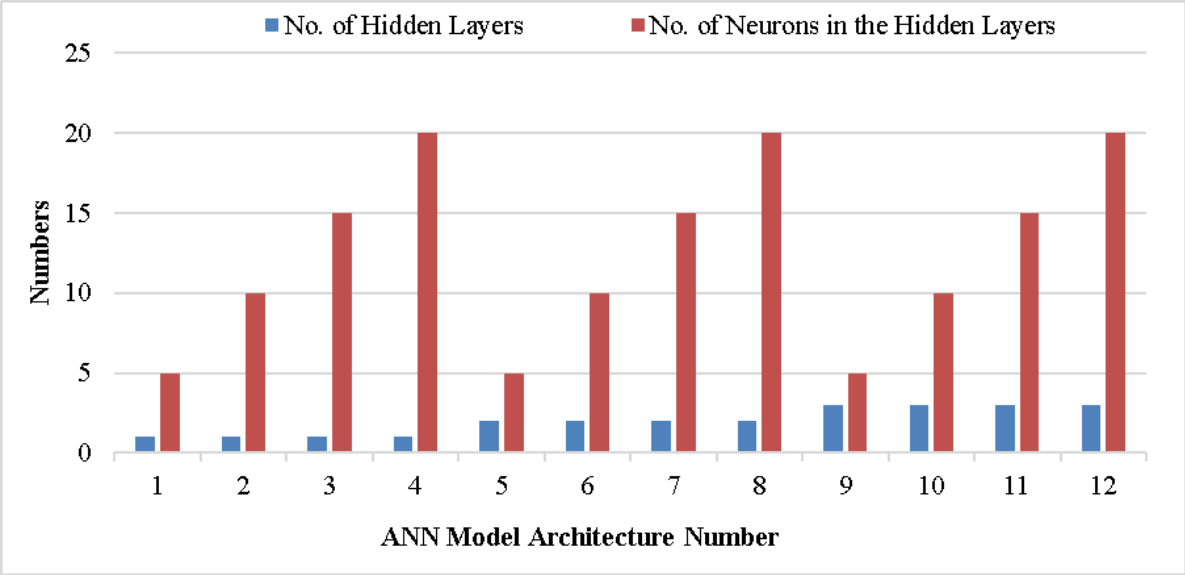


Figure 3 Typical Details of Different ANN Model Architectures of Rutting, Raveling and Cracking

6.2 ANN Learning Process

Back-propagation supervised learning algorithm is used for the ANN distress prediction model development as it is a suitable type of learning for definite input and out variables and in multilayer feed forward neural network architecture. A random sampling method is used to divide the database into training (85%) and validation (15%) datasets. The training data set is used to develop the model, while the validation data is used to assess the accuracy (generalization) of the ANN models and in avoiding overfitting or under-fitting.

6.3 Neuron Activation Function

In this study, a sigmoid function is used as the a neuron activation function because of its support of nonlinearity and its capability for avoiding excessively large its support of nonlinearity and capability for avoiding excessively large values to concise form and differentiability. The output of each neuron calculated by the sigmoid transfer function, which can be expressed using Eqns. 2 and 3.

$$z = f(y) = \frac{1}{1+e^{-a(y)}} \quad (2)$$

$$y = \sum_{i=1}^{n} w_i x_i \quad (3)$$

Where, z = neuron output, y = input to the transfer function, a = gain of the sigmoid function, n = number of elements in the input vector, Xi= ith element in the input vector, and Wi = weight of connection i.

6.4 Results & Findings

Given different ANN model architectures, the precise weights of connections among neurons are settled through the training (trial & error) procedure. The model investigated different ANN architectures for Rut depth, Raveling, Pothole, Cracking and Edge Break models through root mean square error (RMSE) and correlation coefficient (R2) during the training and validation stages. A typical detail of ANN model architecture trials for rut depth is presented in Figure 4.

To optimize the model advance training (deep learning) with higher parameter of gradient descent such as learning rate, momentum and epoch are implemented.

Learning rate is the factor that determines the size of the steps that the network takes in navigating through the weight to minimize the error, which often ranges from 0 to 1. Learning rate determines how fast or slow the network will move towards optimal weight. Learning that is too large can cause a model to converge too quickly to suboptimal solution; whereas a learning that is too small can causes a process to oscillate for longer period and can get stuck. In this study more training and validation is conducted to find the optimal learning rate and momentum that provide the lowest error and highest R2 of models to be developed. A typical training detail on the proposed ANN model architecture for rut depth by changing the momentum and learning rate is shown in Figures 5 and 6.

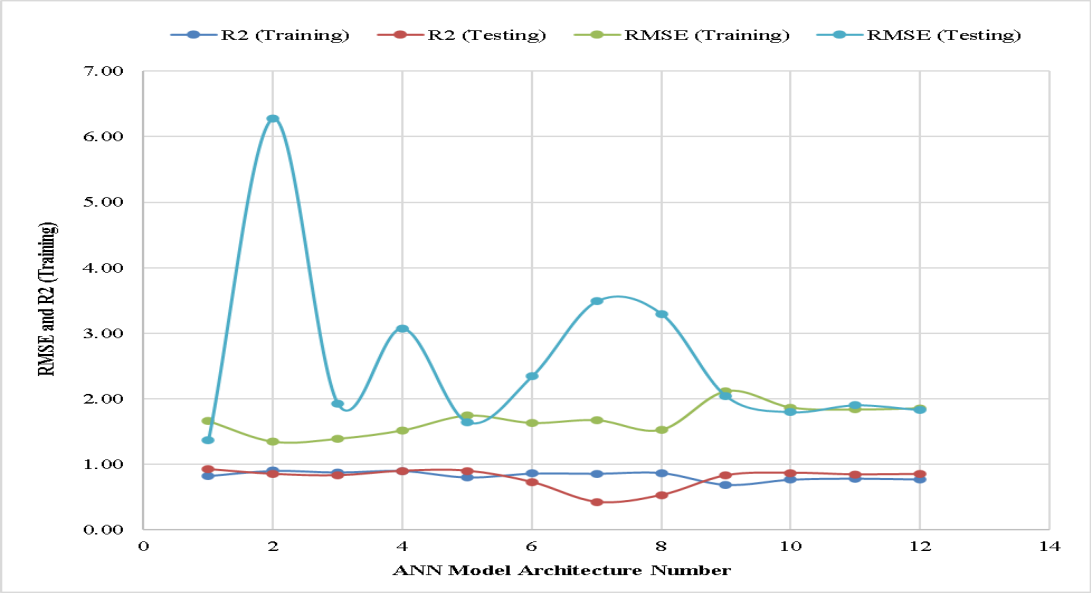


Figure 4 Details of ANN Model Architecture Trials for Rut Depth

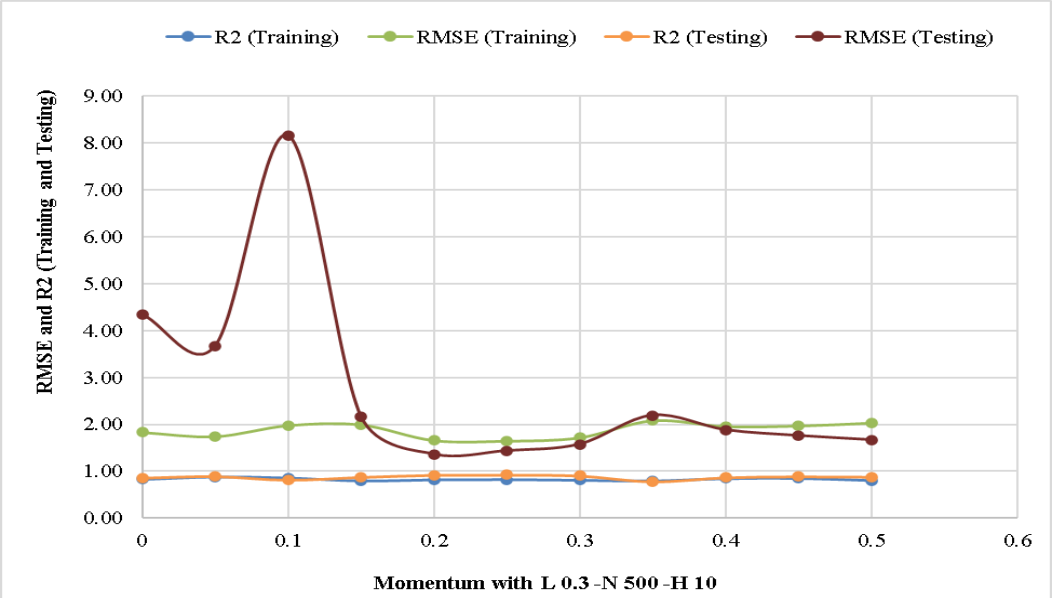


Figure 5 Typical Details of Rut Depth ANN Models at Various Momentums

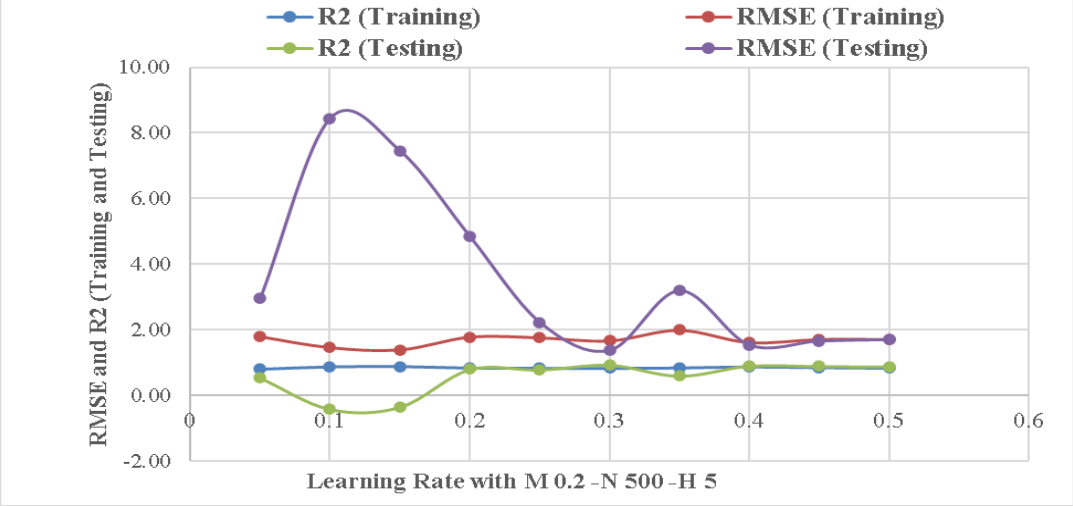


Figure 6 Typical Details of Rut Depth ANN Models at Various Learning Rate

Smaller learning rates require more training epochs given the smaller changes made to the weights on each update, whereas larger learning rates result in rapid changes and require fewer training epochs. This parameter regulates the amount of allocated error to the weight.

Therefore, further training and validation is applied by changing the number of epoch. The typical training details of the proposed ANN model architecture for rut depth was

identified with optimum learning rate of 0.3 and momentum of 0.2 by changing the number of epoch are presented in Figure 7.

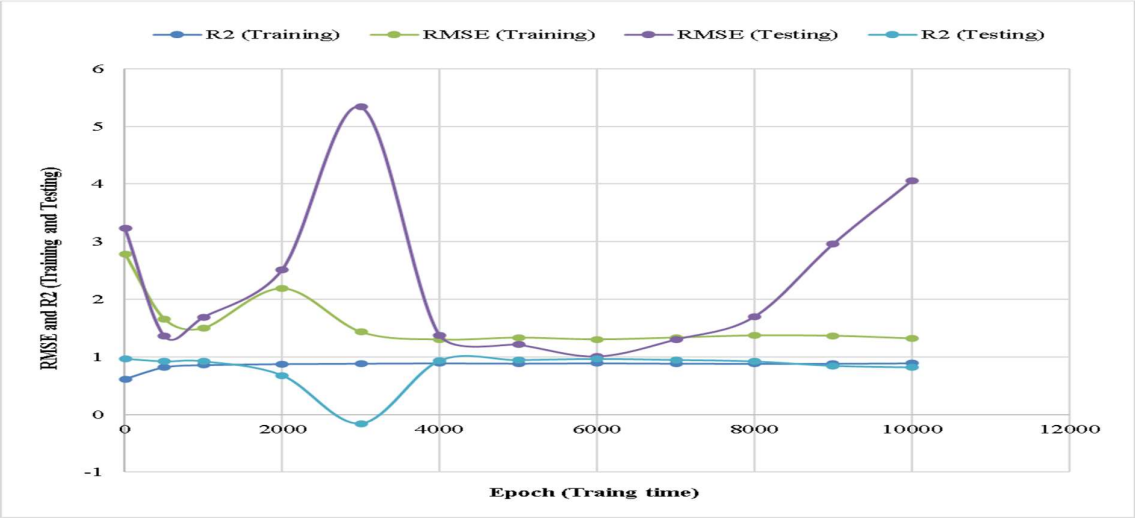


Figure 7 Typical Details of Rut Depth ANN Models at Various Epochs

As illustrated in Figure 4 to 7, 90 iterations are conducted to train and validate the data set. The rut depth ANN model which has an architecture of 5 neurons in a single hidden layer, learning rate of 0.3, momentum of 0.2 and training time (epoch) of 6000 produced smallest training and validation RMSE which is the optimal model in light of greater generalization power associated with fewer hidden neurons. The final proposed rut depth ANN mode network diagram is illustrated using Figure 8.

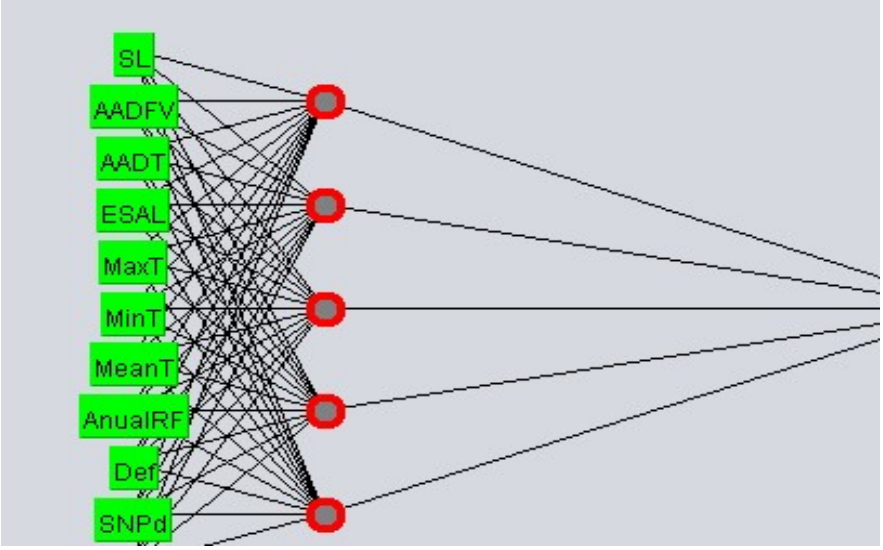


Figure 8 Network Diagram of the Final Rut Depth ANN Model

Based on the results of the network training, two connection weight matrices are derived for the rut depth model as shown in Tables 2 and 3. The weight matrices represent the knowledge abstracted from the training data set.

Table 2 Connection Weight between Input Layers & Hidden Layers of Rut Depth Model

Hidden layers / **Input Layers**	**S N 1**	**S N 2**	**S N 3**	**S N 4**	**S N 5**
Threshold	-1.917	-1.002	-0.865	-2.290	-1.917
SL	-0.096	0.488	6.825	-0.368	8.938
AADFV	1.889	-3.819	4.91	4.742	4.827
AADT	11.183	1.327	9.155	1.778	-0.248
ESAL	3.198	0.007	3.885	1.632	8.2
MaxT	0.057	-0.227	3.95	-2.512	-1.282
MinT	-2.568	6.38	5.236	6.506	1.996
MeanT	-1.401	2.664	5.039	1.891	1.33
ARF	0.635	-5.331	11.427	3.142	1.066
Def	3.604	0.75	1.434	4.51	8.837
SNP	1.92	-0.769	-4.513	3.237	-4.253
DC	15.272	6.275	4.262	5.059	0.623

Table 11 Connection Weight between Hidden and Output Layers of Final Rut Depth Model

	Hidden layer					
	Threshold	N1	N2	N3	N4	N5
Output	-0.7134	1.03	0.92	1.97	-4.2	0.63

6.5 MLP-NN Prediction Models

In this study the same procedure is applied in developing the prediction models for all distresses. This analysis demonstrated the capability of predicting pavement conditions based on several variables or factors affecting distresses using Multilayer Perceptron Artificial Neural network (MLP-ANN) modeling technique and a summary of the ANN distress prediction models are shown in Table 4.

Table 12 Summary of MLP-NN Distress Prediction Model Result

MLP-NN Result	**Type of Model**									
	Rut depth		**Raveling**		**Pothole**		**Cracking**		**Edge break**	
	Training	**Validation**	**Training**	**Validation**	**Training**	**Validation**	**Training**	**Validation**	**Training**	**Validation**
R^2	0.89	0.96	0.97	0.97	0.94	0.97	0.85	0.84	0.93	0.85
RMSE	1.30	1.01	2.5	2.45	68.5	71.9	2.12	1.89	1.39	1.41

An exertion was made to evaluate the relative importance of each input variable in predicting the individual distress modes. In determining the relative importance or contribution of each input/ independent variable in the ANN models, the image of ANN as black box model can be changed using: Garson's algorithm (Eqn. 4). Garson's algorithm utilizes connection weights in links between ANN layers to calculate the relative importance (RI) of input variables on output variables. The RI of each independent variable is reported as a percentage, where the larger RI of a specific factor shows that it has a greater effect on the pavement condition. Because the pavements are not necessarily influenced by every input variable, the relative contributions of input variables that influence on major distresses of AC pavement (rutting, cracking, raveling, pothole and edge break) are described in Figures 9-13.

$$RI = \frac{\sum_{i=1}^{h}\left(W\,i,j\ x\ O\frac{j}{\sum W\,i,j}\right)}{\sum_{1}^{n}(\sum_{i=1}^{h} W\,i,j\ x\ O\,j/\sum W\,i,j)} \quad (4)$$

Where, h = hidden neurons; n = input variables; Oj = connection weight between (j) hidden neurons and the output neuron and h i, j= connection weight values between inputs (i) and (j) hidden neurons

The contributions of AADFV (15.64%), SNP (15.045) and DC (13.12) are the top three influencers on AC pavement rutting, while SL (19%), MinT (15%) and AADT (13%) affect raveling. In addition, SNP (24%), AADT (16%) and ESAL (14%) are relatively the root causes for potholes, while Def. (08%), DC (17%) and AADFV (14%) affect wide cracking. ESAL (27.58%), SNP (15.44%) and ARF (14.7%) are the major causes for edge breaks. Based on the developed models, both the training and validation data set resulted in a coefficient of determination (R2) ranging from 0.84 to 97 which showed a good test of fit.

7 Conclusion

Modeling AC pavement distresses is very essential in road asset and/or pavement management system for prioritizing works & treatment types; allocating funding for maintenance and rehabilitation activities at a network level and; for determining the most cost-effective strategies. The objective of this study is to develop ANN models to accurately predict distresses of AC pavement by using ERA projects as case studies and estimate the relative contribution of input variables or factors affecting pavement distresses.

In this study, five individual Multilayer Perceptron Artificial Neural network (MLP-ANN) based distress prediction models for cracking, raveling, rut depth, pothole and edge break are developed using pavement condition data. The input parameters for each of the five models have been decided on the basis of literature review and available dataset in ERA database. The collected data is divided in two parts: training and validation. Twelve different architectures of ANN models have been tested for each of the five models. The proposed ANN models have also been validated by comparing observed distresses vs. ANN predicted distresses. The goodness of fit (R2) between ANN predicted vs. observed distresses shows a value ranging from 0.84 to 0.97 for all models and hence shows the accuracy of the proposed ANN models.

In this research, eleven parameters were used: Service Life (SL), Average Annual Daily Freight Vehicles (AADFV), Average Annual Daily Traffic (AADT), Equivalent Single Axel Load (ESAL), Mean Annual Temperature (MeanT), Maximum Temperature (MaxT), Minimum Temperature

(MinT), Average Annual Rainfall (ARF), Drainage Condition (DC), Deflection (Def) and Adjusted Structural Number (SNP).

The relative contribution of each factor on pavement distresses has been identified. Based on the relative importance (RI), significant independent variables which affect the different distresses in descending order are: in rut depth model AADFV, SNP, DC, ARF, AADT and SL; in raveling model, SL, MinT, AADT, AADFV and ARF; in pothole model, SNP, AADT, ESAL and AADFV; in cracking model, Deflection (Def), DC, AADFV, ESAL, SNP and MaxT; and in Edge Break are ESAL, SNP, ARF, Def and AADFV.

The findings of this study can be used in future design adjustments and selecting appropriate treatments. The study can enhance current ERA's efforts in pavement management system at a program ad network level. In addition, this study illustrated the capability of ANN as a data analysis & decision-making supporting tool for construction engineering & management practice, which can be applied by local engineers and managers. Furthermore, the application can change the perception that neural network model is a black box model.

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