MODELLING PRESENT SERVICEABILITY RATING OF HIGHWAY USING ARTIFICIAL NEURAL NETWORK

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 ISSN 1923-6654 (print)
ISSN 1923-6662 (online). Available at http://www.ssrn.com/link/OIDA-Intl-Journal-Sustainable-Dev.html

Abstract: Reliable pavement performance prediction models are essential for pavement design and preservation effort. Pavement performance is defined as the serviceability trend of the pavement over a design period of time. Serviceability indicates the ability of the pavement to serve and sustain the demand of the traffic in the existing condition. Pavement condition can be evaluated in four aspects: roughness, surface distress, structural capacity and skid resistance. In the analysis of the results of the road test conducted by American Association of State Highway Officials (AASHO), the subjective evaluation of serviceability by users was called the Present Serviceability Rating (PSR). The data used in modelling Pavement Serviceability Index (PSI), as reported by some authors, violate the basic assumptions of linear regression modelling in that it does not follow normal distribution. The objective of this study is to explore the relationship between the subjective Pavement Serviceability Rating (PSR) and objective index called Present Serviceability Index for highway sections in South-East, Nigeria. Artificial Neural Network (ANN) model was used to explore the relationship. The method of rating PSR is based on a five point scale: 0 – 1 (very good); 1 – 2 (good); 2 – 3 (fair); 3 - 4 (critical) and 4 – 5 (poor). International roughness Index (IRI) was converted to Slope Variance (SV). The input variables are rut depth, cracking, patching and SV. Back-propagation of ANN models with different activation function and number of hidden layers were trained and tested. The dataset was randomly split into three subsets, namely training (60 %), testing (20 %) and validation (20 %) for the ANN model. The optimal models were evaluated with respect to forecasting error and coefficient of determination. Both Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for all predictions are plotted. Considering the architecture (4-18-1) with minimum MAE, RMSE and coefficient of determination, the table and figures show that the topology with one hidden layer with hyperbolic transfer function and hyperbolic transfer function for the output layer is the best. Comparison was made with multiple linear regression model which attempts to obtain a relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. The results showed that the coefficient of determination for ANN model is 0.90 compared to 0.34 for regression model; ANN has demonstrated its ability to model non-linear data. This result confirms that the input variables are non-linear, and the ANN has shown to forecast with high degree of accuracy over regression analysis.

Keywords: Artificial neural network; pavement condition; present serviceability index; pavement serviceability rating; roughness.

INTRODUCTION

Predictions of reliable pavement performance models of road network are important for pavement design and rehabilitation effort [1]. The need for pavement prediction encompasses the financial planning and budgeting function [2]. Pavement performance is described as the serviceability trend of the pavement over the design period [3] One of the objectives of the analyses of the Road test results conducted by American Association of State Highway Officials (AASHO) was the development of a relationship between this subjective rating and an objective index, called the Present Serviceability Index (PSI), which could be calculated as a function of measurements of roughness and distress (rutting, cracking and patching). Pavement condition is a generic phrase to describe the ability of a pavement to sustain a certain level of serviceability under given traffic loadings.

Various indices such as PSI, PSR, Mean Panel Rating (MPR), Pavement Condition Index (PCI), Pavement Condition Rating (PCR), Ride Number (RN), Profile Index (PI), and International Roughness Index (IRI) have been developed to measure pavement performance in either these individual aspects or a combination of them [4,5]. The functional performance index, such as the PSI and IRI, is normally used to characterize the ride quality of a pavement, whereas the structural performance index, such as the Structural Number (SN), is employed to qualify the structural capacity. The objective of this study is to use Artificial Neural Network (ANN) to further explore the relationship existing between the subjective PSR and objective parameters of PSI for 247 sections of the highways in South East of Nigeria.

PSI is predominantly a measure of ride quality rather than surface distress. The original PSI equation for flexible pavement is shown in Eq. (1). IRI and PSI are both index that can be used as indicators of road roughness and serviceability. In Malaysia, the IRI is used widely to measure the smoothness of the asphaltic pavement while the PSI is used to evaluate the functional performance of the pavement [6].

$$PSI = 5.03 - 1.91\log(1 + SV) - 0.01\sqrt{C + P} - 1.38RD^2 \quad (1)$$

Where: SV = Slope Variance [log (1+SV) = function of profile roughness]
C = crack length (in)
P = Patching Area (ft^2)
RD = Rut depth (in)

Composite pavement deterioration models in terms of PSI and PCI was developed for low volume roads in India. An ANN was used to model the PSR for the flexible pavements with input variables as slope variance, rut depth, patches, cracking and longitudinal cracking. The model was trained and tested using 74 samples of data taken from AASHTO test results [7]. Al-Omari and Darter [8] used the database from National Cooperative Research Program (NCHRP) Projects 1 - 23 to establish a formula relating Pavement Serviceability Rating (PSR) and IRI. Hung and Chen [9] explained that the data used in modelling the PSI version [1] violate the basic assumptions of linear regression modelling in that it does not follow normal distribution. In their work they developed three forecasting models for pavement serviceability ratios: fuzzy regression model, a support vector machine (SVM) and a genetic programming. It was reported that SVM model delivered the most accurate estimates of PSR for the PSI of the AASHO panel data. Shah et al., [10] modelled PSI for asphalt pavement sections located in the urban city of Noida, near Delhi, the capital of India. The PSI was developed as a function of the pavement age. An attempt was made to calibrate the AASHTO equation for PSI and its suitability of the equation for Indian pavement conditions for the selected urban roads. New Mexico Department of Transportation (NMDOT) used PSI to express the serviceability level of a pavement section at the network level. The NMDOT uses PSI values to assess their pavement network and to determine funding eligibility of projects for particular roadway sections. The PSI is evaluated from the distress rating and automated roughness and rutting data gathered annually [11]. Al-Khateeb & Khadour [12] developed experimental models for PSI for rural highways in Jordan. Multiple non-linear regression models were developed using data collected on the 35 asphalt pavement sections. The data collected included the PSR, roughness of the pavement represented by the slope variance, and physical measurements of pavements distresses. Rut depth, debonding and potholes (combined as one variable) were the most significant variable that affected the PSI of the pavements having a slope variance less than 500 (1 x 10^{-6} in^2/in^2), whereas, linear cracking and debonding and potholes (combined as one variable) had the highest effect on the PSI of pavements having a slope variance greater than 500 (1 x 10^{-6} in^2/in^2). In another study by Al-khateeb [13] the individual relationships between the PSI and the PSR as dependent variables and the heavy vehicular load-related variables including the percentage of trucks, percentage of heavy trucks, and the percentage of buses were evaluated. The results showed that the measured PSR values for the pavement sections surveyed agreed with the PSI values determined from Al-Khateeb & Khadour [12]. A significant correlation between the percentage of the total trucks and the PSI of rural highway pavements was obtained while increase in percentage of total trucks resulted in a considerable decrease in PSI value. Monica [14] developed models relating the IRI to slope variance (SV) and equivalent single axle loads. The models were developed for road sections in Utah monitored by the Long Term Pavement Performance program of the Federal Highway Administration. The models provide valuable information for conversion from IRI values to SV and vice versa. One of the models fits the boundary conditions of IRI used for this research.

ANN has been used in a wide range of applications in the field of pavement management and engineering. Several models have been developed to predict pavement's conditions as well as to recommend appropriate maintenance strategies. ANN was also used to predict the present serviceability rating (PSR) of pavements [15]. The input variables were structural number, age and cumulative equivalent single-axle loads. Moreover, a partitioning method of connection weights was used to determine the relative contribution of each input variable to PSR prediction. Also, ANNs [16], [5], [17-27] have recently been used in simulating pavement deterioration, pavement-performance predictions, flexible pavement cracking prediction, and condition ratings of jointed concrete pavements. Several ANN studies such as explained above have been used to estimate current pavement conditions, predict future pavement deterioration and to assist engineers in selecting the optimal maintenance and rehabilitation activities.

MATERIALS AND METHODS

The pavement database of the highways in the South East zone of the country was obtained from the Pavement Evaluation Unit (PEU) of the Federal Ministry of Transportation, Kaduna, Nigeria as shown in Table 1. The data include, PSR, pavement condition survey results, Roughness measurements and detailed visual inspection results. The summary of the data is presented in Table 2. The method of rating PSR by PEU is also based on a five point scale but in the reverse order when compared with AASHTO rating: 0 – 1 (very good); 1 - 2 (good); 2 – 3 (fair); 3 - 4 (critical); and 4 - 5 (poor). The model by Monica [14] was used to convert the IRI to slope variance as shown in Eq. 2.

$$IRI = 1.5748e^{0.0339SV} \qquad (R^2 = 0.9818) \qquad (2)$$

Table 1: Summary of the selected Federal highways in South East of Nigeria

S/N	State	Road	No of lanes	Length
1	Abia	Abayi Junction on Enugu-P/Harcourt	4	14km
		Aba-Ikot Ekpene Akwa Ibom South Bound	2	19km
2	Anambra	Onitsha – Awka Enugu South Bound	4	43km
3	Ebonyi	Abakaliki – Nkalagu	2	47km
4	Enugu	9^{th} mile corner- Obollo Afor	2	70km
5	Enugu	Udi-Ozara-Nara-Nkerefi	2	54km

Table 2: Statistical Summary of the data

	Range	Minimum	Maximum	Mean	Standard deviation
IRI	7.20	1.70	8.90	3.723	1.256
PSR	3.00	2.00	5.00	3.380	0.727
CRACKS	21.92	0.00	21.92	10.763	5.078
RUT DEPTH	0.10	0.00	0.10	0.005	0.019
PATCHING	3.40	0.00	3.40	0.347	0.560
SV	48.83	2.26	51.09	23.861	9.379

ANN Model Development

Back-propagation (BP) algorithm type of ANN models was trained with the pavement data to predict pavement serviceability rating. The topology used is shown in Figure 1. The modelling of PSR was implemented using Statistical Package for Social Sciences (SPSS) software which selects optimal neural network architecture. The BP algorithm uses the gradient descent rule for minimization of the error. The dataset was randomly split into three subsets, namely training (60%), testing (20%) and validation (20%) for the ANN model. There are four input variables (SV, cracking, rut depth and patching) and one output (PSR). The error term E is defined in Eq. 3. However, the computed output in the BP algorithm is expressed in Eq. 4.

$$E = \frac{1}{2}\sum_{r=1}^{R}\left(Y_r^m - a_{I:r}^m\right)^2 \qquad (3)$$

Where: Y_r = computed output

a_r = actual output

$$Y_{ik} = \gamma_I\left(\sum_{j=0}^{J_1} W_{I:j,k}\, a_{i-1:j}\right) \qquad (4)$$

Where: $a_{i-1:0} = 1$

γ_i (c) – activation function for layer

W_{ij} – weight of a link connecting

The activation function for both the hidden layers and the output layer was set to hyperbolic tangent and sigmoid function, as defined by the following functions:

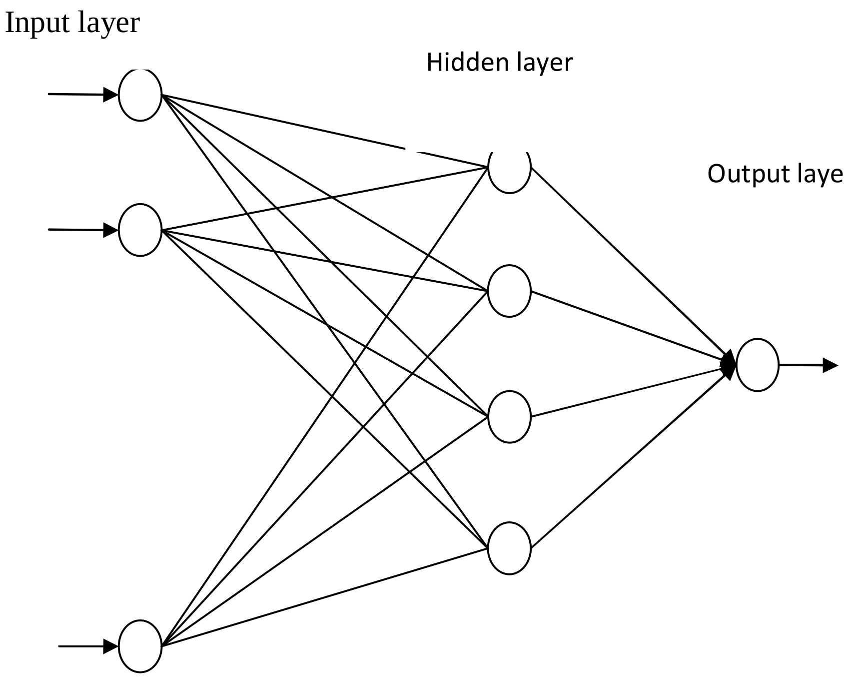

Figure 1: ANN typology of backpropagation for modelling PSR

RESULTS AND DISCUSSION

ANN models were developed using different activation configuration for both the hidden layer and the output layer to identify the minimum forecasting error and the best architecture. The optimal models were evaluated with respect to forecasting error and coefficient of determination (R^2) as shown in Table 3. Both mean absolute error (MAE) and Root Mean Square Error (RMSE) for all predictions are plotted in Figures 2 and 3 respectively. Considering the architecture (4-18-1) with minimum MAE, RMSE and coefficient of determination, the topology for both one hidden layer and the output layer is hyperbolic transfer function, as shown in the table and figures is the best. Regression model was developed to forecast PSR for comparison purpose. The developed equation for determining PSR is given in Eq. (7). The model summary and the analysis of variance are shown in Tables 3 and 4. All the parameters in the PSR model are statistically significant. The coefficient of determination shows that the ANN model has higher R^2 values than that of the regression model. ANN training mechanism is based on pattern recognition and it was observed the neural network was able to learn sufficiently from the given data set resulting in reasonably relative error.

Table 2 ANN Architecture and Forecasting Error for PSR model

Model	Activation	Training Rel. Error	Testing Rel. Error	Validation Rel. Error	MAE	RMSE	R^2	Hidden layer
1	Hyperbolic/ Identity	0.207	0.234	0.993	0.119	0.373	0.792	10
2	Hyperbolic/ Hyperbolic	0.002	0.478	0.558	0.012	0.239	0.901	18
3	Hyperbolic/ Hyperbolic	0.108	0.629	0.262	0.023	0.661	0.829	18-14
4	Hyperbolic/ Sigmoid	0.018	0.467	0.412	0.011	0.295	0.846	18
5	Sigmoid/ Sigmoid	0.175	0.271	0.702	0.009	0.346	0.780	18
6	Sigmoid/ Sigmoid	0.253	0.408	0.661	0.022	0.418	0.700	18-14
7	Sigmoid/ Hyperbolic	0.353	0.391	0.701	0.002	0.439	0.64	18-14

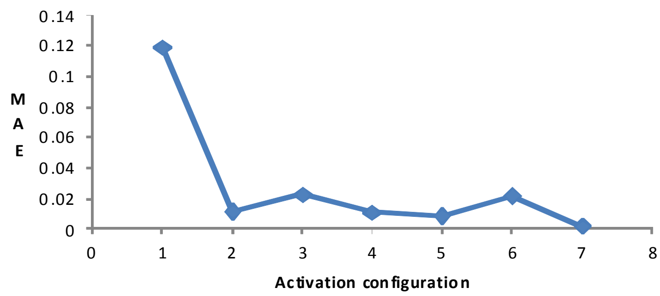

Figure 2 : Mean absolute errors for activation configuration

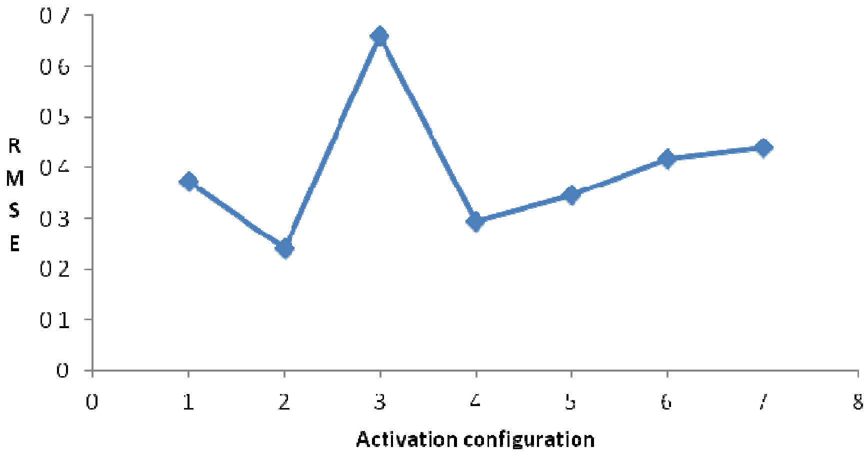

Figure 3 : RMSE for the activation configuration

$$PSR = 2.103 + 0.035SV + 0.035Crack + 0.153Patch + 3.715RutDepth \quad (7)$$

Table 3 Regression Model Summary

Model		Coefficients B	Std. Error	Beta	t	Sig.
R = 0.596	Constant	2.103	0.127		16.527	0.000
R^2= 0.335	SV	0.035	0.004	0.449	8.448	0.000
AdjR^2=0.344	Crack	0.035	0.008	0.243	4.215	0.000
SEE = 0.589	Rut depth	3.715	2.003	0.097	1.855	0.065
	Patching	0.153	0.076	0.118	2.011	0.045

Table 4 Analysis of Variance

	Sum of Squares	df	Mean square	F	Sig.
Regression	46.211	4	11.553	83.314	0.000
Residual	83.923	242	0.347		
Total	130.134	246			

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CONCLUSION

This study presented ANN for modelling subjective PSR and objective parameters of PSI for 247 highway sections in the South East, Nigeria. The ANN models were examined for different activation function and number of neurons in each layer. The model with the minimum MAE and RMSE was the combination of hyperbolic and hyperbolic function for hidden layer and output layer respectively. Regression model was also developed for comparison purpose. The results showed that the coefficient of determination of ANN model is higher than that of the Regression model. This shows the advantage of ANN model to pattern recognition of the dataset and forecast with reasonable accuracy over regression analysis.

ACKNOWLEDGEMENT

The authors wish to acknowledge the Tshwane University of Technology, Pretoria, South Africa for supporting the publication of this paper and the Pavement Evaluation Unit of the Federal Ministry of Transportation, Kaduna, Nigeria for the provision of data used for the study.

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