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APPLICATION OF DYNAMIC ARTIFICIAL NEURAL NETWORK FOR MODELLING RUTS DEPTH FOR LAGOS-IBADAN EXPRESSWAY, NIGERIA

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ABSTRACT

One of the most common distresses on Lagos (the economic nerves centre of Nigeria) and Ibadan the largest city in West Africa Expressway pavement is surface rutting. Rutting makes the road surface uneven, patchy and bumpy and subsequently affects the handling of vehicles which can lead to safety problems. The ability to predict the amount and growth of rutting in flexible pavements is an important aspect of pavement design. This paper presents the results of a research aimed at developing reliable and time - dependent Artificial Neural Network (ANN) based rut depth prediction model for Lagos - Ibadan Expressway. The model incorporate relevant variables such as pavement distresses, pavement layer thickness, pavement roughness, cumulative equivalent single axle load, sub grade California Bearing Ratio (CBR) and overlay asphalt concrete characteristics. The results showed that the forecasting accuracy of the 11-24-1 architecture is high compared with other tested architecture in terms of both average absolute error (AAE) and root mean square error (RMSE). The usage of the model will allow the road agencies to obtain reliable and accurate predictions of the future rut depth of the flexible pavements based on the given input variables.

Keywords: rut depth, artificial neural network, pavement, architecture, forecast.

INTRODUCTION

One of the most common distresses on Lagos (the economic nerve of Nigeria) and Ibadan (the largest city in West Africa) Expressway pavement is surface rutting. Rutting is defined as longitudinal permanent deformation or unrecoverable depression within the pavement layers in the wheel paths after repeated application of axle loading. It may occur in one or both wheel path of a lane (Paterson, 1987; Hwa *et al*., 2005). It can be categorized as either traffic load associated deformation, wear related or the combination of both. The causes include traffic load, age of pavement and deformation of the entire pavement structure or instability in the form of one or more pavement layers. Deformation occurring in pavement layers can be defined in engineering as the critical strain experienced by the top layer of sub grade. Rutting make the road surface uneven, patchy and bumpy and subsequently affects the handling of vehicles which can lead to safety problems.

The ability to predict the amount and growth of permanent deformation or rutting in flexible pavements is an important aspect of pavement design. This is achieved by estimating the cover thickness of high quality materials required to protect the natural sub grade against the compressive stresses from traffic, and thus limiting deformation to within acceptable limits over time. This approach has led to the development of various relationships between acceptable rut depth limits and the various measures of material and traffic properties, enabling the design of adequate pavement structures (Chen *et al.*, 2004). In modern pavement management systems the routine measurement and prediction of rutting on road roughness, dynamic loads and safety (based on the hazard of ponding water), all of which influence the road user costs of vehicle operation and accidents.

Many attempts have been made by both researchers and practitioners alike to develop models that could predict the deterioration of a pavement over time, including models for the prediction of rutting (Zaman *et al.*, 2003). Each model, however, has certain inherent limitations due to the assumptions and data used during development of the model. Two approaches exist to predict rutting as a result of densification and plastic flow. The first approach is mostly used in pavement design procedures and limit deformation to below a specified "failure" limit; these models are not useful for performance modelling because of the need to predict not the limit, but the trend of rutting during the life of the pavement (Paterson, 1987). The second approach predicts the trend of rutting during the life of a pavement, identifying the response of a pavement to actions of traffic, environment and maintenance (Watanatada *et al.*, 1987). As such, this second approach is useful for pavement performance predictions.

This paper presents the result of a research aimed at developing reliable and time - dependent Artificial Neural Network (ANN) based rut depth prediction model for Lagos - Ibadan Expressway. Usage of this predictive model will allow the Road management agency to obtain reliable and accurate predictions of the future condition of the pavement based on measured engineering parameters.

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MATERIALS

Data were collected on the study road for four years on the pavement distress while Roughness Index was obtained from Pavement Evaluation Unit (PEU) of the Federal Ministry of Works, Kaduna. Geotechnical properties of the pavement were obtained from Pentagon Engineering Consultants. The model incorporate relevant variables such as pavement distresses, pavement layers thickness, pavement roughness, cumulative equivalent single axle load, sub grade CBR, and overlay asphalt concrete characteristics (Figure-1).

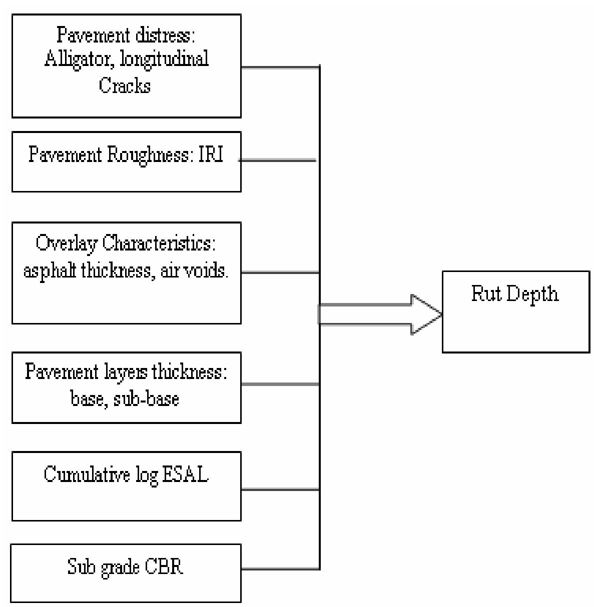

Figure-1. Variables used for pavement rut depth prediction model.

Factors influencing rut depth

Mix design properties

Hot mix asphalt (HMA) pavement mixtures are expected to perform over extended period of time under variety of traffic and environmental conditions. HMA properties are very important in resisting permanent deformation and cracking under traffic loads. The percent of air voids also influences the behaviour of the mix. Numerous studies indicate that the minimum air voids after trafficking should always exceed 3% to avoid potential plastic flow but should be less than 5% to keep hardening of the binder to a minimum. Design information on (voids in mix and the overlay thickness) the study road for this research was obtained from Pavement Evaluation Unit of Federal Ministry of Works.

Pavement layers

Pavement layers and its thickness play a crucial role in bearing and distributing wheel load to the underlying sub grade. More layer or thicker pavement structure would mean least being distributed to the sub grade and subsequently reduce vertical critical strain.

Pavement roughness

Present pavement condition state will influence its future performance. Pavement roughness is an expression of irregularities in the pavement surface that adversely affect the ride quality of a vehicle and its operational costs. Most roughness indicators (International Roughness Index and Ride Quality) represent roughness by the sensation felt by a passenger in a moving vehicle. The pavement is commonly measured in International Roughness Index (IRI), which was developed by World Bank in the 1980s and it is in use by many engineering agencies.

Pavement cracking

Cracking in pavements occurs when a stress is built up in a layer that exceeds the tensile or shear strength of the pavement materials. Cracking may be associated with various distress mechanisms. Cracks provide paths for surface water to infiltrate the pavement structure and cause damage. Crack types include: fatigue cracks, longitudinal cracks, transverse cracks, block cracks, reflective cracks, edge cracks, and slippage cracks (Caltrans, 2000). The increased moisture content due to ingress of water through a cracked surface layer will result in a decrease in shear strength of granular pavement layers which, when over-stressed by traffic, will result in the shear failure of the layers and thus the increased deformation. The major factors affecting the formation of pavement cracking include traffic loading, material properties, and climate.

Traffic loading

The magnitude and number of wheel load passes is the main agent to deteriorate the pavement surface. Heavy and medium trucks normally fitted with large axles would significantly damage the surface as well as deform the underlying pavement layers permanently. Traffic loading is one of the most important factors contributing to rutting. It is important to note that a few excessive loads or tyre pressure for which the pavement was not designed may cause stresses exceeding the shear strength of the material and thus plastic flow, resulting in the premature failure of the layer. The current AASHTO design method based on the total number of passes of the standard equivalent single axle load (ESAL) during the designed period was used in the model development.

Sub grade California bearing ratio (CBR)

The sub grade is the foundation layer over which the roadway is being constructed and all the loads which come onto the pavement are eventually supported by it. In some cases, this layer is normally considered to be the natural in situ; in other cases, the term sub grade is applied to include compacted soil existing in a cut section or the upper layer of an embankment section. The CBR test is taken as direct measure of the strength of the in-situ sub grade material. Despite concerns regarding the limited accuracy of this test, it is utilized on the basis that is

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widely used and accepted by both theorists and practitioners.

ARTIFICIAL NEURAL NETWORK (ANN) BASED MODEL

Neural networks represent distributed parallel information-processing systems that consist of many simple processing elements called neurons. Each neuron is connected to other neurons by means of directed links and each link has a weight associated with it. Each neuron is a processing element that involves a weighted summation plus a function transfer. Due to its differentiability and conciseness in function form, the sigmoid functions (i.e., *logsig* and *tansig*) have been widely employed as the transfer function for real-world applications. The learning capability of a neural network is achieved by adjusting the signs and magnitudes of its connection weights according to certain learning rules that seek to minimize a cost or error function. The Back-propagation (BP) method, employed in this study, is the most widespread learning rule for network training. Two steps are involved in the training process.

In the first step, the training patterns compiled from a data source are fed into the input layer of the network. These inputs were then propagated through the network until the output layer is reached. The network output is compared to the observed value.

In the second step, the above error is minimized by back-propagation of the calculated error through the network. During this process, the individual error contribution caused by each layer is computed and distributed backward and the corresponding weight adjustments are made to minimize the error.

The weights are updated according to a specified learning algorithm during the training process that uses exemplar data. The resultant connection weights expressed in form of matrix represent the knowledge gained by a network after many loops of training epochs. Training is considered complete when the overall error is reduced to an acceptable level. Upon completion of training, a neural network extracted the underlying information contained in the training data, acquired the ability of generalization, and is ready for prediction of unseen data trend.

To apply neural networks for solving a particular real-life problem, appropriate architecture needs to be designed based on the characteristics of the particular phenomenon being modelled.

The neural network toolbox embedded in Mat lab was chosen to be the modelling tool for this study due to its flexibility in structure specification and implementation of various training algorithms. Dynamic ANN-based training technique was utilized to model the time-dependent pavement rut depth (Najjar, 1999; Najjar and Zhang, 2000).

Architecture design and training of neural networks

Architecture of ANN is not a straight forward decision making process, it is most times, trial and error combined with engineering judgement to determine the appropriate architecture for a particular problem. Significant effort was made to determine the best architecture for the ANN model. This includes input and output variables, number of hidden layers and number of hidden neurons in each hidden layers (Figure-2). Table-1 shows the training and testing errors resulting from architectures for 3-years rut depth forecasting model.

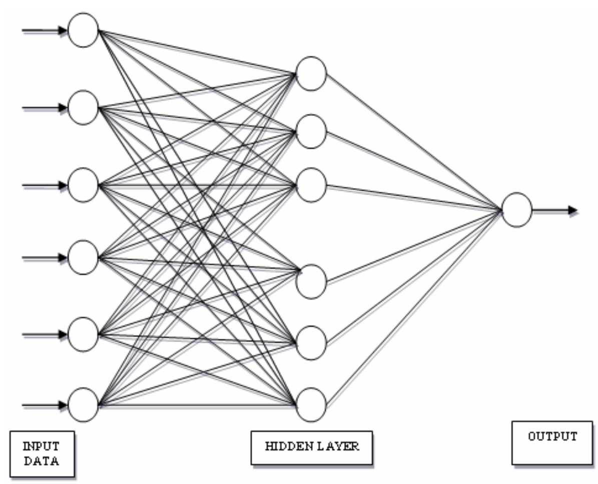

Figure-2. Schematic of the architecture of a typical back-propagation ANN.

PERFORMANCE EVALUATION OF THE ANN MODEL

The training and testing process enables the neural network attains the capabilities simulating the amount and growth of permanent deformation and forecasting of the future permanent deformation. The next step is to evaluate the performance of the developed neural network model. Varying numbers of hidden layers were used to train the network and the optimal number of nodes in the hidden layer is chosen on the basis of least testing error as presented in Table-1. The overall forecasting error indicates that the 24-hidden layer has higher forecasting accuracy than other hidden layers tested for the multiple years. The performance of the forecasting model was further assessed with respect to the goodness of fit measure (R^2). Figure-3 represents the results for coefficient of determination for each of the hidden layers for the three years consecutively.

Table-1. Forecasting errors of different network architectures.

No. of Neurons	year	AAE	RMSE	MARE
24	1st year	0.162	15.001	5.822×10^{-3}
	2nd year	0.156	15.816	4.380×10^{-3}
	3rd year	0.152	18.446	4.398×10^{-3}
27	1st year	0.627	13.660	6.598×10^{-3}
	2nd year	0.316	16.514	4.701×10^{-3}
	3rd year	0.518	26.708	6.305×10^{-3}
28	1st year	0.587	12.438	5.600×10^{-3}
	2nd year	0.317	17.759	4.780×10^{-3}
	3rd year	0.442	20.214	4.654×10^{-3}
29	1st year	0.320	14.840	7.120×10^{-3}
	2nd year	0.450	19.365	5.720×10^{-3}
	3rd year	0.590	21.638	5.680×10^{-3}

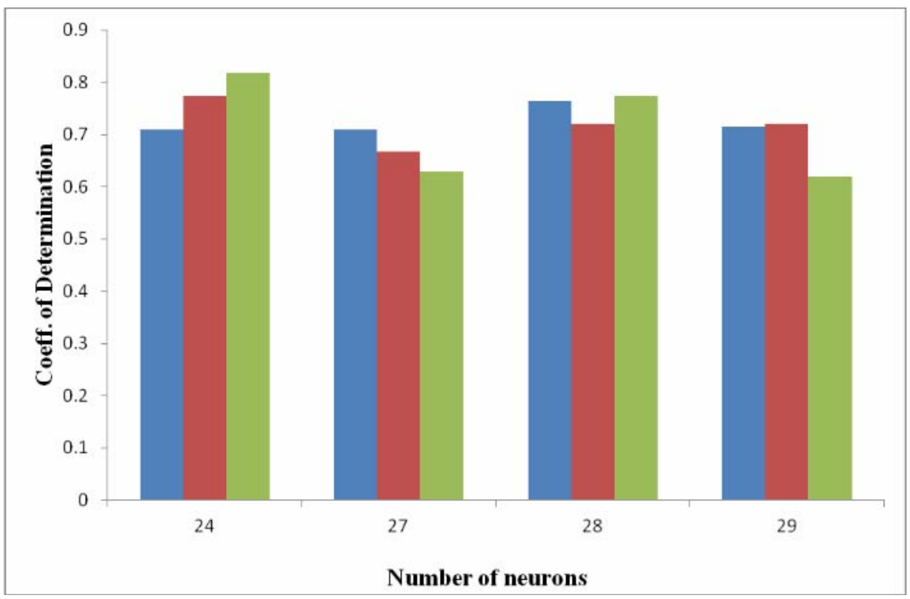

Figure-3. Coefficient of determination against number of neurons.

DISCUSSIONS OF RESULTS

The performance comparison of the hidden layers indicates the forecasting accuracy of the 11-24-1 architecture is high compared with other tested hidden layers in terms of both average absolute error (AAE) (see equation 1) and root mean square error (RMSE) (see equation 2). Also, as the forecasting period becomes longer the error also increases. The 11-24-1 architecture shows that as the year increases the coefficient of determination (R^2) also increases thus showing how well the model predicts the rut depth and the adequacy of the overall model (Figure-3). The implication of this study is that dynamic ANN is appropriate for use to forecast rut depth for multiple steps. In addition, the parallel computation structure of ANN allows for easy capture of non-linearity underlying the training data. The rut depth prediction model can be used for designing purpose and in the choice of construction materials.

$$AAE = \frac{\sum |O - P|}{N} \quad \ldots 1$$

$$RMSE = \sqrt{\frac{\sum (O - P)^2}{N}} \quad \ldots 2$$

$$MARE = \frac{1}{N} \sum_t \frac{\left| x(t) - \bar{x}(t) \right|}{x(t)} \quad \ldots 3$$

CONCLUSIONS

This paper summarizes the research efforts and the findings of using dynamic artificial neural network in modelling rut depth of flexible pavement in Nigeria. The model incorporate relevant variables such as pavement distresses, pavement layer thickness, pavement roughness, cumulative equivalent single axle load, sub grade CBR and overlay asphalt concrete characteristics. Architecture with 11-24-1 shows a high forecasting accuracy compared with other tested architecture. The coefficient of determination increases with multiple years forecasting thus showing how well the model predicts the rut depth. The usage of the model will allow the road agencies to obtain reliable and accurate predictions of the future rut depth of the flexible pavements based on the given input variables.

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