Prediction of rutting deterioration in flexible pavements using artificial neural network and genetic algorithm

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ABSTRACT

Rutting is one of the major deteriorations of asphalt pavement, significantly impacts road safety and service quality. Prediction models are necessary to prevent and control the damage caused by this deterioration in the pavement management system. In this study, using the artificial neural network algorithm, models have been developed to predict the amount of rutting deterioration using the long-term pavement performance (LTPP) database. These models have been developed for wet freeze, dry freeze, and dry no freeze climates. Since proper accuracy and simplicity are the most important features of a prediction model, using the NSGA II-MLP multi-objective optimization method, the more important variables in predicting rutting deterioration are identified and selected as the model input. Then, using traffic, climatic and structural variables selected from the genetic algorithm, rutting deterioration prediction models were developed. The coefficient of determination and the mean squared error for the model made in the wet freeze zone and the model of dry freeze and dry no freeze zones are equal to 0. 96, 2.05, 0.94 and 3.45, respectively. Also, by performing sensitivity analysis, the effect of input data of each model on rutting deterioration was determined. The cumulative maximum and minimum daily temperature difference per year, pavement age, asphalt layer thickness, annual equivalent single axle loads, and bitumen penetration are the most impactful variables that have the greatest impact on rutting deterioration.

KEYWORDS

Rutting, flexible pavement, artificial neural network, multi-objective optimization, genetic algorithm

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1. Introduction

Asphalt pavements are part of the national assets of each country, which must be maintained at an acceptable level of service [1]. One of the main deteriorations of asphalt pavements is rutting, which is caused by the accumulation of permanent deformations in the pavement layers [2]. One of the pavement management system (PMS) tasks is to determine the optimal maintenance time by predicting the pavement future condition [3]. Using pavement failure prediction models, the pavement status in the future is determined, and the pavement management system based on the results of these models helps managers choosing the right time to repair the pavement in the appropriate service conditions [4].

In recent studies in this field, Radwan et al. [5] Developed models for predicting rutting failure in dry no freeze and wet no freeze climates. In this study, stepwise regression analysis was performed to obtain the factors affecting the model. In this model, the coefficient of determination is 0.479 for dry no freeze zones and 0.233 for wet no freeze zones. In recent studies, machine learning methods have been used to predict pavement condition. Zeiada et al. [6] have used various machine learning methods such as support vector machines, regression tree, artificial neural network, etc., to predict the international pavement roughness index. Comparing the results, it was observed that the artificial neural network had the highest accuracy compared to other methods, including linear regression.

This study aims to develop a model for predicting the rutting depth using an artificial neural network. To find the effective parameters, the NSGA II-MLP algorithm based on the neural network has been used. Due to the lack of coherent and reliable information about the condition of pavements in Iran, in this study, long-term pavement performance (LTPP) data has been used, and the impact of various factors such as weather, traffic, and pavement structures on the rutting failure has been investigated.

2. Methodology

In this study, 377 asphalt pavement sections have been selected from asphalt concrete pavement sections on unbound and bound bases. In this research, the rutting depth variable has been used as an output variable, and various climatic, traffic and pavement structure variables have been used as inputs to create a data set. Structural variables and material characteristics include type of base, specific gravity of asphalt and bitumen, percentage of air and bitumen in asphalt mixture, material size, bitumen stiffness, thickness of different pavement layers, drainage conditions, resilient modulus, specific gravity and moisture of subgrade, and pavement age. The equivalent single axle load is used as traffic variable. Climatic variables include air temperature, freeze and thaw indices, humidity, shortwave radiation on the surface, cloud cover, and precipitation.

Artificial neural network algorithms are one of the most efficient and popular machine learning tools. Artificial neural networks work based on the physiological structure and mechanism of the human brain and can solve complex problems with high accuracy. This study used a multilayer perceptron neural network to develop a prediction model. The basis of the operation of these methods is that first random values for weights and bias are considered, and by performing the network, modeling error is obtained. Then, with the backward propagation of the error in the network, the weights and the bias are changed to reduce the error in the next prediction cycle [7].

To develop an efficient model that has the features of simplicity and ease of use while being accurate, it is necessary to identify the variables that are more important in predicting rutting failure. For this purpose, an optimization problem is defined with two objective functions: the first objective function is to minimize the number of input variables and the second objective function is to maximize the accuracy of the neural network model. Using NSGA II-MLP method, input data of models related to each of the considered climatic zones were selected. Finally, by using selected input variables and training neural networks with them, the desired models for wet freeze zone and the model of dry freeze and dry no freeze zones have been developed [8].

There are several statistical indicators to evaluate the accuracy of the models. In this study, the accuracy of the models was evaluated using the coefficient of determination (R^2) and mean absolute error (MAE). Equations (1) and (2) show how to calculate these indicators [9].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|T_i - \bar{T}_i\right|\right) \tag{1}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(T_i - \bar{T}\right)\left(P_i - \bar{P}\right)}{\sqrt{\sum_{i=1}^{n}\left(T_i - \bar{T}\right)^2 \sum_{i=1}^{n}\left(P_i - \bar{P}\right)}}\right)^2 \tag{2}$$

Where P is the predicted value, $\bar{P}$ is the average of the data predicted by the model, T is the target value, $\bar{T}$ is the average value of the target data, and n is the number of data.

3. Result

Using NSGA II-MLP algorithm, in wet freeze zones (first zone) with seven input variables and in dry freeze and dry no freeze regions (second zone) with eight variables, the accuracy of the models has reached the maximum value. The variables selected in the first zone include pavement age, freeze and thaw index, equivalent single axle load, maximum and minimum daily temperature difference, asphalt layer thickness, percentage of materials passing through sieve #4 (4.75 mm) and maximum specific gravity of the subgrade. The variables of the second zone also include the first five variables mentioned for the previous zone. In addition, the base type, bitumen penetration, and percentage of materials passing through sieve #4 and residue on sieve #200 in asphalt mixture are among the variables in this zones.

To better evaluate the performance of the neural network, R^2 and MAE of the three categories of training, testing and validation data for each model have been calculated separately. Table 1 shows the values of the statistical indices of the first and second zone models.

Table 1. statistical indices of developed models

Name	type	MAE	R^2
First zone	Training	0.84	0.94
First zone	Testing	1.44	0.88
First zone	Validation	1.65	0.88
Second zone	Training	0.62	0.96
Second zone	Testing	2.16	0.84
Second zone	Validation	2.11	0.94

Since it is impossible to understand the relationship between input and output variables in the artificial neural network modeling method, by sensitivity analysis, the effect of input variables of each model on the rutting failure was determined. Among the variables that have the greatest impact on rutting deterioration in the first zone are the cumulative maximum and minimum daily temperature difference per year, pavement age, and asphalt layer thickness. Also, in the second zone, important variables include equivalent single axle load, bitumen penetration, and asphalt layer thickness.

4. Conclusions

The concluding remarks of this study are as follows:

- The important role of NSGA II-MLP method in selecting effective input variables and thus creating a model with less complexity and input variables has been identified. Using this method, optimal models were created by considering more effective variables in each model to predict rutting deterioration in the studied climatic zones.
- The coefficient of determination for the models made in the wet freeze and the common model of dry freeze and dry no freeze zones are equal to 0.96 and 0.94, respectively. This indicates that the artificial neural network can predict rutting failure behavior well.
- It was concluded that depending on the weather conditions, various factors can affect the rutting performance. The variables of pavement temperature and age in the first zone and the variables of traffic load and bitumen penetration in the second zone were more important than other variables.

5. References

[1] T.F. Fwa, The handbook of highway engineering, CRC press, 2005.

[2] B. Ali, Numerical Model for the Mechanical Behavior of Pavement: Application to the Analysis of Rutting, PhD, University of Science and Technology Lille, France, (2006).

[3] K.H. McGhee, Automated pavement distress collection techniques, Transportation Research Board, 2004.

[4] K.A. Abaza, Deterministic performance prediction model for rehabilitation and management of flexible pavement, International Journal of Pavement Engineering, 5(2) (2004) 111-121.

[5] M. RADWAN, A.-H. Mostafa, M. HASHEM, H. FAHEEM, Modeling pavement performance based on LTPP database for flexible pavements, Teknik Dergi, 31(4) (2020) 10127-10146.

[6] W. Zeiada, S.A. Dabous, K. Hamad, R. Al-Ruzouq, M.A. Khalil, Machine learning for pavement performance modelling in warm climate regions, Arabian journal for science and engineering, 45(5) (2020) 4091-4109.

[7] E. Heidari, M.A. Sobati, S. Movahedirad, Accurate prediction of nanofluid viscosity using a multilayer perceptron artificial neural network (MLP-ANN), Chemometrics and intelligent laboratory systems, 155 (2016) 73-85.

[8] M. Ehsani, F. Moghadas Nejad, P. Hajikarimi, Developing an optimized faulting prediction model in Jointed Plain Concrete Pavement using artificial neural networks and random forest methods, International Journal of Pavement Engineering, (2022) 1-16.

[9] Z. He, X. Wen, H. Liu, J. Du, A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region, Journal of Hydrology, 509 (2014) 379-386.