Amirkabir Journal of Civil Engineering

Amirkabir J. Civil Eng., 54(7) (2022) 515-518
DOI: 10.22060/ceej.2021.19406.7161

Faulting Prediction Model in Jointed Plain Concrete Pavement and determining the parameters affecting this failure with Artificial Neural Networks

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ABSTRACT: Faulting is one of the most common functional failures in concrete pavements. Pavement design and pavement management systems can both benefit from predicting this failure. Therefore, predicting this failure can be very useful. Artificial neural networks, a powerful technique, were utilized in this study to predict this failure. The artificial neural network architecture was first determined by trial and error using 32 input variables such as traffic, weather, and structural data, and then the defined architecture was appropriately trained. New input factors that have not been explored before, such as Poisson's ratio and elastic modulus of concrete slabs, have been considered among these 32 variables, in addition to the variables utilized in earlier studies. After that, 19 input variables were discovered using a new method, and a new neural network model with 19 variables was created. Notably, the feature selection method used in this study has been developed using the metaheuristic optimization algorithm. For the model with 32 variables and 19 variables, the correlation coefficient, mean square error, and mean absolute error are 0.97, 0.45, 0.43, 0.95, 0.54, and 0.6, respectively. Random forest is recognized in data mining as a powerful technique for identifying the importance of input variables. Finally, the importance of 19 variables was assessed using the random forest approach, with the four most important variables being the yearly cumulative number of days with precipitation more than 12.7 mm (24%), elastic modulus (14%), pavement life (12%), and base thickness (10%). It is found that elastic modulus is an essential input factor that has not been considered in prior studies.

Review History:

Received: Dec. 21, 2020
Revised: Feb. 11, 2021
Accepted: Nov. 27, 2021
Available Online: Dec. 20, 2021

Keywords:

Jointed Plain Concrete Pavement (JPCP)
Faulting Failure
Artificial Neural Networks (ANN)
Feature Selection
Machine Learning

1- Introduction

The most popular type of rigid pavement is Jointed Plain Concrete Pavement (JPCP) [1]. Multiple factors such as traffic loading, severe weather conditions, pavement materials qualities, and pavement structure design cause various distress such as faulting in JPCP over time. The variation in height across a transverse joint is known as faulting. One of the most severe structural problems of JPCP is faulting [2]. Pavement maintenance must be done at the right time. In the pavement management system (PMS), timing is crucial since late maintenance may quadruple the entire cost. To avoid a threefold rise in costs, on-time maintenance operations necessitate accurate forecasting of the number of distinct distresses at any given stage [3]. As a result, developing failure prediction models, such as faulting distress, is critical for making Maintenance and Rehabilitation (M&R) technique decisions and estimating pavement life.

Artificial intelligence (machine learning) has been used to solve pavement engineering problems in recent years. Saghafi et al. [4] projected faulting by considering several input factors such as age, base type, base thickness, erodibility class, percent passing sieve #4 and #200 for base materials, and resilience modulus of the base layer. They employed multivariate linear regression (MLR) and artificial neural networks (ANNs) to anticipate faulting, which yielded R^2 values of 0.51 and 0.94, respectively. Wang and Tsai [5] looked at many factors, including cumulative ESAL, age, etc. They partitioned the variables into four groups and used the ANNs approach to create four models. Their overall model (which included all variables) showed more minor error than the other three, but none of their models were very accurate.

This research aim is to use the ANN approach to forecast faulting failure. Initially, 32 input factors that impact are chosen from the authors' and literature's perspectives, and a general prediction model is built. The feature selection problem was then handled using the metaheuristic optimization approach, and 19 factors causing this failure were found. The 19 variables introduced are used to create a new prediction model. Finally, the Random Forest approach is used to discover crucial factors of this failure.

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2- Methodology

133 Jointed Plain Concrete Pavement (JPCP) sections were selected from the long-term pavement performance (LTPP), and the amount of faulting failure was extracted over time. The faulting variable is used as the response variable in this study. Input variables have been considered in this study, which includes: Base thickness multiplied by resilient modulus (BM), base and drainage type (BND, DRG, and DRGT), mean transverse joint spacing (JSP), slab, base, and subbase thickness (STH, BTH, and SBTH), dowel (DWL), Poisson's ratio (PR), elasticity modulus (EM), tensile strength (TS), and compressive strength of concrete slab (CS), cumulative and annual average ESALs (CESAL and ESAL), age (ND), climate zone (WNF, DNF, FT, and DF), cumulative and annual average freeze-thaw (FT and CFT), cumulative and annual average number of days when the temperature is higher than 32 degrees of centigrade (D32 and CD32), cumulative and annual average number of days when the precipitation is more than 12.7 and 0.25 mm (CINT and INT), cumulative and mean freezing index (CFI and FI), and cumulative and annual average precipitation (CPRC and PRC). The data are divided into training (70%), validation (15%), and test (15%) sections to develop the prediction models.

ANNs are one of the most helpful and efficient machine learning technologies accessible. According to the nature of the problem, this tool is known as a machine learning approach for predicting output(s) in regression problems. ANNs inspired by the human brain can accurately model a wide range of very complicated nonlinear problems [6]. The general model is developed with 32 input variables and determines the best architecture for ANN.Variables impacting faulting failure should be discovered to design a basic and forecasting model. For this purpose, a combination of NSGA II optimization method and ANN technique has been used. This study employed two objective functions to choose the attributes that have the greatest influence on faulting failure. The first objective function (F1) seeks to reduce the number of input variables, while the second seeks to reduce the ANN error (F2). This problem was solved using an integer optimization problem. There were 32 decision factors (equal to the total number of input variables). Each choice variable can have a value of zero or one as the solution in this issue. "Zero" indicates that the variable is not chosen, whereas "One" indicates that it is significant. A simple model is designed to predict faulting with selected variables after determining the features affecting faulting.Random Forest (RF) is one of the machine learning ensemble techniques that can determine the importance of input variables [7]. This research determined the importance of the selected variables from the feature selection problem using the RF method.

Finally, the accuracy and inaccuracy of the created models may be assessed using a variety of statistical measures. To evaluate each model constructed in this work, the R-squared (R2) and mean absolute error (MAE) were utilized. Eqs. (1) and (2) show how mean absolute error (MAE) and R-squared (R2) calculate to evaluate models [8].

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

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

Where T is the target value (measured), P is the predicted value, $\overline{T}$ is the average value of the target data, $\overline{P}$ is the average of the data predicted by the model, and n is the number of data examined.

3- Results

After solving the feature selection problem, it was found that ND, FT, WF, WNF, DNF, DF, D32, WT, CINT, CD32, CESAL, DWL, DRG, JSP, SBTH, BTH, STH, PR, and EM variables have a significant effect on faulting failure. The general model with 32 input variables and the simplified model with 19 selected input variables were developed. The results of these models are reported in Table 1.

Also, the importance of the selected variables was determined by the random forest technique. The results show that the yearly cumulative number of days with precipitation more than 12.7 mm (24%), elastic modulus (14%), age (12%), and base thickness (10%) variables have the most significant impact on faulting failure and should be controlled.

4- Conclusions

The following are inferences that can be drawn:

The feature selection method presented in this study selected 19 input variables and constructed a simplified model. The accuracy of the simplified model is very appropriate, which indicates the high accuracy of the feature selection method.

Table 1. Performance evaluation of models

Name	type	MAE	R^2
General	Training	0.15	0.98
General	Testing	0.43	0.94
General	Validation	0.46	0.94
Simplified	Training	0.17	0.98
Simplified	Testing	0.6	0.9
Simplified	Validation	0.3	0.94

Yearly cumulative number of days with precipitation more than 12.7 mm, elastic modulus, age, and base thickness variables have the most role in causing faulting failure, respectively.

Using the LTPP data, the approach outlined in this research may be applied to different pavement distresses.

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HOW TO CITE THIS ARTICLE

M. Ehsani, F. Moghadas Nejad, P. Hajikarimi, Faulting Prediction Model in Jointed Plain Concrete Pavement and determining the parameters affecting this failure with Artificial Neural Networks, Amirkabir J. Civil Eng., 54(7) (2022) 515-518.

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