Climate and traffic input based International Roughness Index (IRI) prediction model for rigid pavements using Artificial Neural networks (ANN)

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ABSTRACT: The International Roughness Index (IRI) is a widely used measure of the roughness of road surfaces and ride quality. The Federal Highway Administration (FHWA) has required States' Departments of Transportation (DOT) to include IRI values in their Pavement Management Systems (PMS) since 1990. However, IRI data collection can be challenging due to cost and resource constraints. This study presents an IRI prediction model for rigid pavements for three south Atlantic states of North Carolina, South Carlina, and Virginia. Utilizing climate and traffic data from the Long-Term Pavement Performance (LTPP) database, an Artificial Neural Networks (ANN) was developed to predict IRI. The R^2 for the developed model is 0.84. Sensitivity analysis of the model showed that climate factors have more influence on IRI. In addition, a closed-form standalone equation is also extracted from the model, which Local transportation agencies can leverage to predict IRI using available climate and traffic data.

1 LITERATURE REVIEW

The highway agencies identified roughness as the primary indicator for pavement performance from the early ‘80s but faced inconsistencies in measurement methods. To address this issue, the National Cooperative Highway Research Program and the World Bank standardized a new roughness measuring method known as the International Roughness Index (IRI), ensuring reproducible results across different equipment. Since then, IRI has been widely adopted to assess pavement roughness and ride quality. The Federal Highway Administration has made it mandatory for State Departments of Transportation to include IRI values in their respective Pavement Management System. Therefore, the IRI prediction model is a highly investigated research area.

Compared to flexible pavements, little research has been done on developing IRI prediction models for rigid pavements. The Mechanistic-Empirical Design Guide (MEPDG) has an IRI prediction model for rigid pavement. Initial IRI is an input parameter in that model with transverse cracking, spalling, and patching. There are also site factors in the model, such as pavement age, freezing index, and subgrade property. With the recent development of ANN, several researchers have utilized it for IRI prediction. (Abd El-Hakim and El-Badawy, 2013) employed the same input variables of the MEPDG empirical model with a database of 184 data points to develop the IRI ANN forecast model. The ANN model provided a better R^2 of 0.828 than the MEPDG regression model with R^2 of 0.643. Similarly, several studies showed the potential of ANN for predicting IRI in recent years, utilizing climate and traffic data, and offering more enhanced prediction neural network models. (Sultana *et al.*, 2021) explored the impact of climate attributes and traffic loads on pavement distress, focusing on the IRI as a key indicator of pavement condition. An ANN approach is used to develop IRI prediction models for Jointed Plain Concrete Pavement (JPCP), considering the maintenance and rehabilitation history of the pavements. The best-performing ANN model achieved a high R^2 value of 0.87, successfully estimating IRI values over time and after maintenance activities.

In recent years, researchers have also applied different machine-learning techniques to predict the IRI of rigid pavements. (Wang *et al.*, 2017; Luo, Wang and Li, 2022; Ji *et al.*, 2024) developed a hybrid machine-learning model to predict IRI of Jointed Plain Concrete Pavement (JPCP), the study also compared several machine learning methods, such as eXtreme Gradient Boosting (XGBoost), Gradient Boosting Decision Tree (GBDT), multiple linear regression (MLR), and support vector machine (SVM). The stacking fusion model, combining GBDT and XGBoost as base learners with bagging as meta-learners, outperformed individual models with an RMSE of 0.040, R^2 of 0.996, and MAE of 1.3%, indicating the model improvement.

The ongoing progress of the IRI prediction models for rigid pavements is significant. However, from the construction and maintenance practitioners' point of view, a simpler and more accurate prediction method is required without expert knowledge of machine learning. Therefore, this study aimed to develop an IRI prediction model and extract a closed-form equation from the model, which pavement engineers can utilize without any prior knowledge of Artificial Neural Networks. With the help of the linear equation, pavement engineers can predict the IRI of a particular rigid pavement and plan more cost-effective maintenance and rehabilitation work programs.

2 OBJECTIVES

The objective of this study is to develop a prediction model using ANN for rigid pavement for three South Atlantic states in the wet no-freeze climate zone. From the model, a closed-form stand-alone equation can be extracted, which will work as a proxy for the complex machine learning model for practitioners. Moreover, sensitivity analysis of the prediction equation will be performed to identify the effect of input variables on the IRI of rigid pavement.

3 DATA COLLECTION, SELECTION, AND PROCESSING

For pavement construction, upkeep, and management, it is essential to comprehend how traffic and weather affect IRI in rigid pavements (Hossain, Gopisetti and Miah, 2020). The weather, traffic, and IRI data for the three South Atlantic states - North Carolina, South Carolina, and Virginia were collected from LTPP. Figure 1 shows the three states considered in this study. A total of 120 data points from these three states were utilized to train the model. As IRI decreases during the maintenance process of the pavement surface. Pavement sections that undergo maintenance and rehabilitation processes were excluded from the datasets.

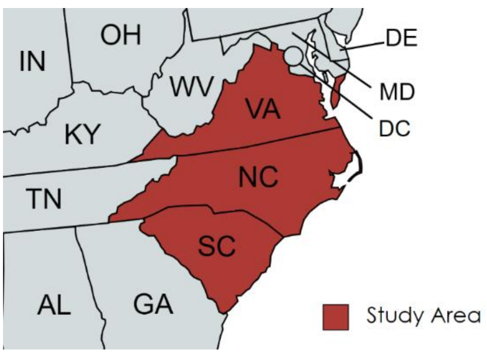

Figure 1. The three South Atlantic states are considered in the study.

In this study, the IRI of rigid pavement is predicted using weather conditions and traffic flow factors. These factors include the proportion of Annual Average Temperature, Equivalent Single Axle Load (ESAL), Average Humidity, Total Annual Precipitation, Previous IRI data, and GESAL (General Equivalent Single Axle Load)

Annual Average Temperature is the temperature experienced over a year in a certain area, typically expressed in degrees Celsius or Fahrenheit. In pavement engineering, this measure is frequently used to evaluate how temperature variations affect pavement performance, including thermal cracking and rutting.

Equivalent Single Axle Load (ESAL) Measures the cumulative damage caused by traffic loading on the pavement. It represents the impact of repeated wheel loads over time, converted to a standard axle load.

The average relative humidity of the air in a particular area over one year is expressed as a percentage. This parameter is frequently used to evaluate how moisture affects pavement performance, including moisture-related distress and degradation.

The total quantity of precipitation that falls at a certain area over a year represents Total Annual Precipitation. It includes rain, snow, and other types of moisture. The moisture level of the pavement layers, which can affect pavement performance such as rutting, cracking, and frost damage, is a crucial parameter in pavement engineering.

The term "Previous IRI" refers to the IRI value that was previously measured or noted at a certain location. This metric is used to measure the success of prior pavement maintenance or rehabilitation efforts as well as the state of a pavement surface.

GESAL (General Equivalent Single Axle Load) is a parameter that is calculated similarly to ESAL (Equivalent Single Axle Load) but uses constant LEF (Load Equivalency Factor). Unlike ESAL, GESAL is independent of pavement type, thickness, and level of distress and can be used to compare traffic loads and their effects on pavement performance between different sites.

As one of the primary areas of research of the Strategic Highway Research Program (SHRP), the Long-Term prediction of the International Roughness Index (IRI) in rigid pavement using machine learning and environmental factors is a challenging task, but it can be achieved with appropriate data collection and modeling techniques. To begin, it is essential to gather a comprehensive dataset that includes the IRI values for the rigid pavements and the corresponding environmental factors.

In this study, the IRIs measured in the left and right wheel paths are employed, and the average IRI values are chosen as the primary factor. Table 1 shows the minimum, maximum, average, and standard deviation of the collected data.

Table 1. Descriptive Statistics of the Model.

Inputs	Minimum	Maximum	Average	Standard Deviation
Temperature (°C)	12.10	18.60	15.23	1.00
Humidity (%)	61.50	74.00	6.25	2.53
Precipitation (mm)	696.30	1,436.90	370.30	177.98
ESAL	18,735	9,33,000	4,57,132	1,74,340
GESAL	25,405	7,39,377	3,56,986	1,31,338
Previous IRI	1.03	2.23	0.60	0.27

4 ARTIFICIAL NEURAL NETWORK IRI MODEL DEVELOPMENT

Artificial Neural Network is a branch of machine learning techniques that work similarly to the human brain. It works as a mathematical function with three layers (input, hidden, output) that process the information through weighted connections. The hidden layer transforms the data utilizing weights and biases while the output layer produces final predictions. The weights and biases are continuously adjusted during learning phases to optimize the network's performance. One of the primary objectives of this study is to derive an IRI prediction equation from the trained ANN model. It was essential to simplify the model network while preserving the accuracy of the predictions. Consequently, a neural network comprising a single hidden layer with three hidden neurons was chosen.

The architecture of the ANN model is shown in Figure 2. The neurons in the hidden layer are connected to each input using weights and biases.

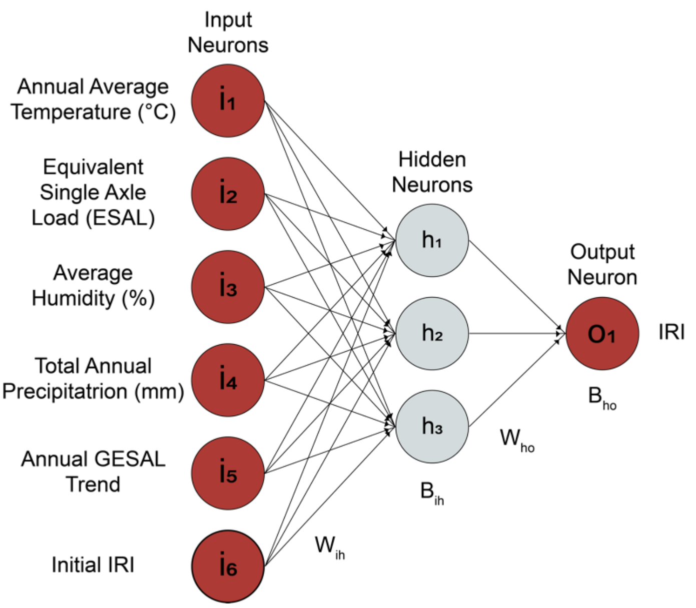

Figure 2. The Architecture of the ANN model.

W_{ih} and B_{ih} stand in for the hidden layer's weights and biases. The hyperbolic tangent function is used as an activation function in the hidden layer. The hidden layer's neurons are connected with the output neuron with weights and bias - W_{ho}, B_{ho}, respectively.

The model used only the rigid pavements satisfying the climate condition of Wet No Freeze was used for this study. In the model training process, each input was normalized between [-1,1] in the input layer. After passing through the input layer, the data moves on to the hidden layer. The output layer receives the transformed data from the hidden layer and produces the final output of the ANN model. The final output is then compared with the measured value of IRI, and the error is calculated. This error is fed into the model and backpropagated to the input layer, adjusting its weights and biases with respect to error. One forward propagation and backpropagation is called an epoch. In the validation process, the objective is to minimize the Mean Squared Error (MSE). In the developed model development process, the average coefficient of determination (R2) was between 0.70 to 0.84. After Multiple iteration of model training the best performed model were selected for equation development.

In the model development process, the standard 70-15-15 approach was used, where 15% of the data points were for model validation, 70% of the data points were for model training, and 15% of the data points were left out for testing. The testing is performed to evaluate the model performance for data outside the training set. This serves the main goal of the study, which is to develop a robust model. Multiple models were created in that process and one model with optimum prediction performance is reported. Figure 3 shows the best-performed model with a coefficient of determination (R^2) = 0.84, Mean Absolute Error (MAE) = 0.12, and Root Mean Square Error (RMSE) = 0.219 for overall datasets.

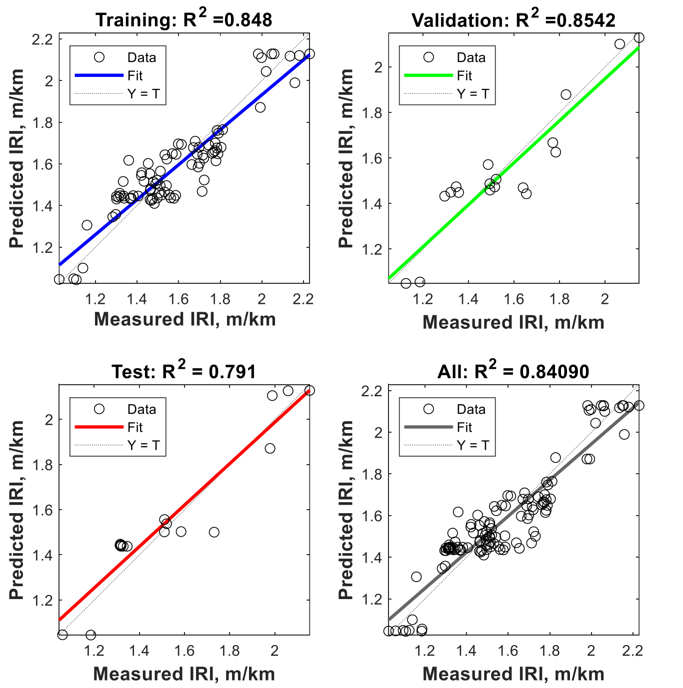

Figure 3. Coefficient of determination of Training, Validation, Testing, and overall dataset.

For practitioners and engineers, a simple linear equation from the developed ANN model is extracted. This simple equation will predict IRI, which is similar to the ANN. Equation 1 is the equation extracted from the model.

$$IRI = 0.6 \times (0.4358 \times (\tanh (1.3907\, \theta + 0.2735\, H + 0.0038\, P - 2.748\, ES - 6.8248\, GS + 0.3087\, IRI_{prev}) + (- 0.2940 \times (\tanh (1.499\, \theta + 0.0133\, H + 0.0021\, P - 7.4161\, ES + 1.2243\, GS - 5.1211\, IRI_{prev}) + (- 0.617 \times (\tanh (- 0.8883\, \theta + 0.0973\, H - 0.0005\, P + 3.4712\, ES - 5.3669\, GS + 0.9939\, IRI_{prev}) - 0.2113 + 1) + 1 \qquad (1)$$

Where IRI = International Roughness Index (m/km); IRI_{prev} = Previous year IRI (m/km); θ = Annual average temperature (°C); G = Annual GESAL; H = Annual average humidity (%); P = Annual average precipitation (mm); E = Annual ESAL

5 SENSITIVITY ANALYSIS OF THE DEVELOPED ANN MODEL

The process of sensitivity analysis is crucial for studies that involve multiple input variables. It helps to determine which independent variables have the most significant impact on the dependent variable and which ones have the least (Ahmed, Isied and Souliman, 2024). The results of the sensitivity analysis in Figure 4 show that the IRI for rigid pavement is more sensitive to humidity, temperature, and precipitation and least sensitive to ESAL.

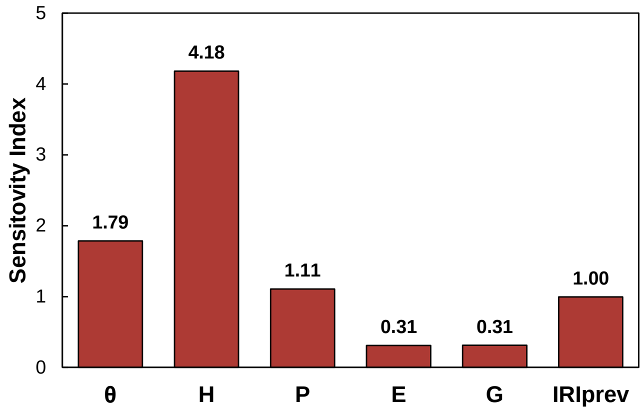

Figure 4. The Architecture of the ANN Model

6 CONCLUSIONS

The International Roughness Index (IRI) prediction model for rigid pavement is developed with the available climate and traffic data for the wet, no freeze climatic conditions for three South Atlantic states - North Carolina, South Carolina, and Virginia. This ANN-based prediction model is developed after training, validation, and testing using LTPP data with R^2 of 0.84. The constructed model can be utilized to forecast the IRI in the traffic and climatic conditions of these states.

The sensitivity analysis shows that the climatic variables have the most effect on the output of the model compared to the traffic-related variables.

Additionally, unlike previous studies, a closed-form standalone equation is extracted from the model. This equation will enable the practitioner to apply the model in practical cases without expert knowledge of machine learning. Future recommendations would involve incorporating more data reflecting various pavement conditions, along with other essential input factors such as the pavement age, aggregate gradation, etc.

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