Roughness Modeling for Composite Pavements using Machine Learning

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Abstract. A large number of paved highway surfaces comprises composite pavements as a result of concrete pavement rehabilitation that uses an asphalt overlay on top of the concrete surface. Annually, billions of dollars are spent on the maintenance and rehabilitation of road networks. Roughness is one of the several indicators of road conditions used to make objective decisions related to road network management. The irregularities in the pavement surface affecting the ride quality of road users can be described by a standard roughness index defined as the International Roughness Index (IRI). Roughness prediction models can identify rehabilitation needs, analyze rehabilitation effects, and estimate future pavement conditions to implement different Maintenance and Rehabilitation (M&R) activities to extend the pavement life cycle and provide a smooth surface for road users. This study intended to develop pavement performance models to predict roughness for asphalt overlay on concrete pavement sections using the Long-Term Performance Pavement (LTPP) program database. Artificial Neural Networks (ANNs) approach was used to develop roughness prediction models. A total of 52 pavement sections with 592 data points were analyzed. Five models were developed, and the best performing model, Model 5 was found with an average square error (ASE) of 0.0023, mean absolute relative error (MARE) of 12.936, and coefficient of determination ($R^2$) of 0.88. Model 5 utilized one output variable (IRIMean) and 14 input variables (i.e., Initial IRIMean, Age, Wet-Freeze, Wet Non-Freeze, Dry-Freeze, Dry Non-Freeze, Asphalt Thickness, Concrete Thickness, CN Code, ESAL, Annual Air Temperature, Freeze Index, Freeze-Thaw, and Precipitation). The ANN model structure utilized for Model 5 was 14-9-1 (14 inputs, 9 hidden nodes, and 1 output). Environmental impacts and traffic repetitions can cause severe damage to the pavement if timely maintenance and rehabilitation are not performed. By considering the effects of the M&R history of the pavement, it is possible to obtain realistic prediction models for future planning. Therefore, the developed ANN roughness performance models in this paper can be used as a prediction tool for IRI values and guide decision-makers to develop a better M&R plan. Local and state agencies can use available historical traffic and climatological data in the developed models to estimate the change in IRI values. Utilizing these prediction models eliminates time-consuming data collection and post-processing, and consequently, a cost reduction. This low-cost tool will improve the condition assessment and effective M&R scheduling.

1. Introduction
An efficient and safe transportation network for public mobility and freight transportation is an important part of a nation’s economy and prosperity [1]. From the 2.6 million miles of paved roads and highways in the United States, 93 percent of them are surfaced with asphalt [1]. However, a large...
portion of the paved highway surfaces comprises composite pavements, which are made of an asphalt overlay on concrete pavements. Most of the composite pavements are a result of concrete pavement rehabilitation [2]. When concrete pavements start to fail, they are overlaid with a hot mix of asphalt (HMA) [2]. The use of composite pavements compared to flexible or rigid pavements, can provide better levels of performance both structurally and functionally and accordingly can be a more cost-effective alternative [2]. Annually, billions of dollars are required for the maintenance and rehabilitation of road networks. If timely maintenance and rehabilitation are not performed, the pavement damages inflicted by environmental impacts and traffic repetitions may lead the pavement to poor conditions that can cause life-threatening for road users [1].

Pavement performance modeling is an important part of pavement management systems (PMS), which allows decision-makers a better budget allocation plan for future pavement maintenance and rehabilitation (M&R) actions [3]. However, current pavement performance prediction models do not account for the influence of M&R activities during the service life of the pavement, which can affect the accuracy of the predictions [3]. Pavement roughness models are necessary to identify rehabilitation needs, analyze rehabilitation effects, and estimate future pavement conditions to implement different M&R activities to extend the pavement life cycle and provide good surface quality for road users [4, 5]. The International Roughness Index (IRI) is accepted as an important indicator of pavement performance and used as the standard for pavement roughness [6]. The objective of this paper is to develop a pavement roughness model using ANNs approach for asphalt overlay on concrete pavement sections in the LTPP database. An IRI prediction method was proposed based on the analysis of the influence of pavement structure, climate, and traffic data.

2. Objectives
The main objectives of this paper are to:

1) Analyze roughness data for asphalt overlay on concrete pavements in the U.S. territories using the Long-Term Performance Pavement (LTPP) database.
2) Develop a roughness model for asphalt overlay on concrete pavements using the Artificial Neural Networks (ANNs) approach on the LTPP database.
3) Perform a sensitivity analysis on one section of the database.

3. Scope
The scope is limited to asphalt overlay on concrete pavements

4. Literature Review
4.1. Literature Review of LTPP Program
The mission to study pavement performance and promote extended pavement life across the United States had been advanced since the late 1950s. Congress authorized the LTPP program as part of the first Strategic Highway Research Program (SHRP) in 1987 [7]. A 5-year applied research program funded by the 50 States through a dedicated share of the Highway Trust Fund [7]. The objectives of the LTPP program were to collect and store performance data from a large number of in-service highways over an extended period to support analysis and product development. Also, analyze the collected data to describe pavements' performance and translate these insights into usable engineering products related to pavement design, construction, rehabilitation, maintenance, preservation, and management [7]. The data collection started in 1989 and 2,509 pavement test sections were selected or constructed for the study.

4.2. Literature Review of International Roughness Index
Roughness is an indicator of road conditions and is useful for making objective decisions related to the management of road networks [8]. Pavement roughness describes the irregularities in the pavement
surfaces that affect the ride quality experienced by daily road users [1]. In 1982, the World Bank and the government of Brazil proposed the International Road Roughness Experiment (IRRE) to find a standard roughness index appropriate for the many types of roughness to provide a basis for comparing roughness measures obtained by different procedures. The IRRE results showed that a standard roughness index was practical, and an index was proposed, the IRI. The IRI is based on the quarter-car analysis method, a mathematical model of a vehicle that represents a body and a single wheel [9], with standardized parameter values and a reference simulation speed of 80 km/h [8]. The IRI measurement can be expressed in two types of units, in/mile or m/km. A higher IRI value indicates a rough pavement profile, which results in a lower ride quality experienced by road users. A lower IRI value indicates a smooth pavement profile, causing a better ride quality for the road users.

4.3. Literature Review of Roughness Models

Recently, several studies showed interest in developing pavement roughness prediction models for both flexible and concrete pavements.

Kargah-Ostadi [10] developed an ANN model for IRI prediction of flexible pavements using a specific pavement study (SPS-5) from the LTPP database. The objective of the study was to use the model to predict and compare pavement roughness variation trends after various rehabilitation alternatives. The optimum ANN structure had eight input variables, five hidden nodes within one hidden layer, and one output. Model testing resulted in the prediction of IRI with minimal errors and future roughness prediction trends that match perfectly with the observed values. These findings indicate that the ANN model performs successfully in predicting IRI trends following each kind of treatment in the SPS-5 experiment.

Hossain et al. [11, 12] developed an ANN prediction model for IRI for both flexible and concrete pavements using climate and traffic data collected from the LTPP database. Seven independent variables were considered as input parameters for predicting IRI. Both models compared the ANN predicted IRI and measured IRI for flexible and rigid pavements under specific climatic zones (wet-freeze for flexible pavement and wet non-freeze for rigid pavement). Both ANN models used a two hidden-layered ANN structure with seven independent variables, nine hidden nodes for the first hidden layer, nine hidden nodes for the second hidden layer, and one output (7-9-9-1), using a nonlinear transfer function. Both studies indicated that the IRI prediction was reasonable for both short-term and long-term predictions using only climate and traffic data.

Mohamed Jaafar [1] developed mechanistic-empirical models using ANN and multiple linear regression techniques for predicting IRI, rutting, and cracking for asphalt pavements using the LTPP database. For the IRI modeling, the ANN architecture used seven independent variables, five hidden nodes, one hidden layer, and one output (i.e. 7-5-1 ANN structure). The ANN model showed a high coefficient of correlation (R) of 0.72. A multiple linear regression model was also developed. An R²-value of 0.63 was found using multiple linear regression. The results show that both ANN and multiple regression models were reasonably accurate for IRI prediction in asphalt pavements.

Khattak et al. [13] developed IRI prediction models using regression analysis for overlay treatment of composite and flexible pavements in the state of Louisiana. For the composite pavement, an R² of 0.63 was found using nine input variables. For the flexible pavement, an R² of 0.47 was found using seven input variables. The study concludes that the developed IRI models provided good agreement between the measured and predicted IRI values with most of the predictions within 5%.

Literature review to date indicates that most roughness prediction models did not consider M&R history as an independent variable. This study proposes the use of CN as a categorical variable in the IRI prediction model for composite pavements. This approach was recently used in an asphalt
highway pavement performance study at the University of Mississippi [1]. This paper developed a pavement roughness prediction model using the ANNs approach for asphalt overlay on concrete pavement sections in the LTPP database.

5. Model Development
5.1. Data Collection
Using the LTPPInfoPave™ database [14], a total of 311 sections were identified with asphalt and concrete in the same section. The asphalt thickness varies from 0.1 to 13.3 inches. The concrete thickness varies from 6.4 to 20.5 inches. Sections that have an asphalt layer thickness equal to or greater than three inches were considered as composite pavement sections. Following this criterion, 272 sections were identified as composite pavement sections with a total of 16,842 IRI measurements from 1989 to 2018. Each section has two types of IRI measurements, IRI$_{Left}$ and IRI$_{Right}$. A mean roughness index (IRI$_{Mean}$) was calculated by averaging the IRI$_{Left}$ and IRI$_{Right}$ measurements. On each visit date, several IRI measurement runs were done for each section. By averaging the IRI measurement runs, a single IRI measurement was obtained for IRI$_{Left}$, IRI$_{Right}$, and IRI$_{Mean}$ for each visit date. A total of 3,304 IRI measurements for 272 sections were obtained. For this study, a total of 592 datasets from 52 different sections were used to develop the ANN IRI prediction model. Figure 1 shows the 592 IRI$_{Mean}$ measurements for the 52 sections.

![Figure 1. IRI$_{Mean}$ Measurement (m/km)](image)

5.2. Consideration of M&R Treatment in the Development of IRI Roughness Prediction Model
The CN is the attribute that LTPP uses to monitor and identify M&R in each section of the database. A CN1 is assigned when the pavement section was opened to the traffic. When an M&R is conducted, the CN number will change from CN1 to CN2. Thus, the CN factor indicates that a major M&R treatment was conducted on the pavement section. The treatment intervention generally improves the pavement condition and performance for roughness, cracking, faulting, joint deterioration, and other surface defects. For this reason, it is imperative to consider CN as a factor for a more realistic and accurate model. For the ANN model development, CN will be used as a categorical variable with a value of zero or one. A zero value is assigned if no M&R was implemented in that section and a value of one is assigned if there was an M&R intervention. The use of M&R actions in the model development was expected to result in more realistic models considering that M&R actions affect the future condition of the pavement. As an illustration, Figure 2 shows different CN values for section 06-7455 located in California. This section has three construction numbers (CN1, CN2, and CN3), which were assigned in 1989, 2001, and 2010.
It is evident from Figure 2 that the M&R treatments improved the composite pavement condition, which contributed to lower IRI values. The IRI values decreased 54% from CN1 (1.185 in 2000) to CN2 (0.541 in 2001) when maintenance and rehabilitation (M&R) were performed in the section. To support this statement an independent sample t-test was performed to determine whether there are statistically significant differences between the means of IRI measurements between CN1 and CN2. The results show that the difference in the means of CN1 IRI Mean and CN2 IRI Mean are statistically significant at $\alpha = 0.05$ probability of chance error. This implies that both IRI Mean samples (CN1 and CN2) are from different populations. Thus, M&R treatments significantly improved the pavement surface condition and contributed to lower IRI values.

6. ANN Model

6.1. Overview of ANN

Artificial Neural Networks is a predictive modeling technique based on mathematical operations that use the concept of human cognition and neural biology [15]. The ANNs approach attempts to emulate the structure and/or functional aspects of biological neural networks [16]. It consists of several simple processing elements called neurons (or nodes) and connection links between them [15]. When the information is processed, the connection links are used to transfer signals between neurons [15]. Complex relationships that are difficult to be identified using traditional sequential, logic-based modeling and computational techniques can be successfully represented by neural networks [15]. There are many types of neural networks characterized by their architecture, training algorithm, and activation function [17]. In this study, a feed-forward neural network with a back-propagation training algorithm was used for the development of the roughness prediction model. Different variable types that contain both categorical and continuous variables were used, and one hidden layer was considered in the model development. The use of more than one hidden layer combined with an insufficient number of databases may cause the network to memorize the data in the training phase [18]. Therefore, the developed models used only one hidden layer to maintain the generalization capability of the network [18]. The TR-SEQ1 computer program [19] was used to develop the ANN models in this study. A sigmoidal function is used for data generalization purposes.

6.2. ANN Model Variables and Architecture

IRI was used as a dependent variable (i.e. output) and several independent variables (i.e. inputs) were used in this study. Some variables were included based on previous literature studies and new variables were introduced in this research. For this paper, five models were tried using different independent and dependent variables. Table 1 shows the variables used for each ANN model in this study.
Table 1. Independent and Dependent Variable Configuration for Five ANN Models.

| Models | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|--------|---------|---------|---------|---------|---------|
| I_0 Left | I_0 IRI\text{mean} | I_0 Left | I_0 IRI\text{mean} | I_0 IRI\text{mean} | I_0 IRI\text{mean} |
| I_0 Right | Age | I_0 Right | Age | Age | Age |
| Age | Wet-Freeze | Age | Wet-Freeze | Wet-Freeze | Wet-Freeze |
| Wet-Freeze | Wet, Non-Freeze | Wet-Freeze | Wet, Non-Freeze | Wet, Non-Freeze | Wet, Non-Freeze |
| Wet, Non-Freeze | Dry-Freeze | Wet, Non-Freeze | Dry-Freeze | Dry-Freeze | Dry-Freeze |
| Dry-Freeze | Dry, Non-Freeze | Dry-Freeze | Dry, Non-Freeze | Dry-Freeze | Dry, Non-Freeze |
| Dry, Non-Freeze | h_{asphalt} | Dry, Non-Freeze | h_{asphalt} | h_{asphalt} | h_{asphalt} |
| h_{asphalt} | h_{concrete} | h_{asphalt} | h_{concrete} | h_{asphalt} | h_{concrete} |
| CN Code | ESAL | CN No Action | CN Any Action | ESAL | ESAL |
| ESAL | | CN Any Action | ESAL | | |

Model 1 used eight input variables, however, the climatic region is used as a categorical variable with four categories. The CN code has a value of 0 for no CN changes and 1 for any changes. Therefore, the first model had 11 input variables and 2 output variables (IRI_{\text{left}} and IRI_{\text{right}}). Model 2 used I_0 IRI_{\text{mean}} instead of I_0 Left and I_0 Right for the input variable. A total of 10 input variables and 1 output variable (IRI_{\text{mean}}) were used. Model 3 used a total of 12 input variables and 2 output variables. The CN was considered as two categorical inputs, CN No action (1 or 0) and CN Any Action (1 or 0). Model 4 used 11 input variables and 1 output variable. Model 5 included climatological factors using a total of 14 input variables and 1 output variable (IRI_{\text{mean}}). All variables used in the model developing for this paper are not related to distresses data, which needs a lot of work, equipment, time, and money to be measured. The ANN models developed in this study used easily available variables that normally most agencies have the records of.

6.3. ANN Model Selection

The best model was selected based on the lowest average square error (ASE), lowest mean absolute relative error (MARE), and highest coefficient of determination (R^2). Table 2 shows statistical measures of the ANN model development stages (i.e., training, testing, validation, and all data) for the five developed models. The final structure of each model is written at the bottom row in an order that depicts the number of inputs, hidden nodes, and output(s), respectively.

Table 2. ANN Model Results.

| Model | MODEL 1 | MODEL 2 | MODEL 3 | MODEL 4 | MODEL 5 |
|-------|---------|---------|---------|---------|---------|
| Network | 1-9-20000 | 1-9-20000 | 5-9-20000 | 1-7-20000 | 1-9-11000 |
| MARE | 13.540 | 16.539 | 14.058 | 15.481 | 15.076 |
| Training | R^2 | 0.83629 | 0.83525 | 0.85762 | 0.84083 | 0.84757 |
| ASE | 0.002775 | 0.003288 | 0.002362 | 0.003064 | 0.002899 |
| MARE | 17.772 | 18.878 | 17.629 | 24.457 | 22.209 |
| Testing | R^2 | 0.70008 | 0.62038 | 0.68056 | 0.54602 | 0.66829 |
| ASE | 0.004578 | 0.006705 | 0.005393 | 0.009307 | 0.00722 |
| MARE | 20.199 | 21.822 | 18.133 | 21.763 | 23.282 |
| Validation | R^2 | 0.5498 | 0.62044 | 0.52444 | 0.50833 | 0.47758 |
| ASE | 0.007772 | 0.007641 | 0.008425 | 0.008617 | 0.009888 |
| MARE | 16.069 | 16.137 | 15.096 | 18.212 | 12.936 |
| All Data | R^2 | 0.77346 | 0.78018 | 0.78704 | 0.7188 | 0.87741 |
| ASE | 0.003659 | 0.004087 | 0.003466 | 0.005285 | 0.002272 |
| Final Structure | 11-9-2 | 10-9-1 | 12-9-2 | 11-7-1 | 14-9-1 |
All the 592 datasets were used to retrain the network at its optimal structure and iteration to obtain the generalized response throughout the complete database. All data stage for Model 5 outperformed all other models with significant improvements on model accuracy measures. For this reason, Model 5 was chosen as the best performing ANN model. Figure 3 shows the network structure of Model 5.

![Network Architecture of the Best Performing ANN Model (Model 5)](image)

**Figure 3.** Network Architecture of the Best Performing ANN Model (Model 5)

### 7. Results and Discussions

Figure 4 shows the accuracy measures of all the developed ANN models for the All Data stage. The accuracy measures show reliable results for all models developed. However, Model 5 results outperform all other models developed. Model 5 has an ASE value (0.0023) 38% lower than the second-lowest ASE value (0.0035, Model 3); a MARE value (12.94) 14% lower than the second-lowest MARE value (15.10, Model 3); a $R^2$ value (0.88) 11% higher than the second-highest $R^2$ value (0.79, Model 3).

![Graphical Comparison of Accuracy Measures between Developed ANN Models](image)

**Figure 4.** Graphical Comparison of Accuracy Measures between Developed ANN Models

Observed IRI$_{\text{mean}}$ values collected from the LTPP database and the predicted IRI$_{\text{mean}}$ predictions using Model 5 are presented in Figure 5. The plot shows the IRI$_{\text{mean}}$ (m/km) values in the y-axis and a section sequence number (generated to identify the data points in the database) on the x-axis.

![Comparison of Observed and Predicted IRI$_{\text{mean}}$ Measurements (m/km)](image)

**Figure 5.** Observed and Predicted IRI$_{\text{mean}}$
Lower IRI\textsubscript{Mean} values were better predicted than higher values. Figure 6 shows that Model 5 predictions clustered around the line of equality, but the predicted values are closer to the observed values until the IRI\textsubscript{Mean} value is equal to 3 m/km. When the observed IRI\textsubscript{Mean} value is greater than 3 m/km, the model was not as accurate as it was for lower IRI\textsubscript{Mean} values. Nevertheless, a high R\textsuperscript{2} of 0.88 was obtained for the ANN Model 5.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure6.png}
\caption{Observed vs. Predicted IRI\textsubscript{Mean} for ANN Model 5}
\end{figure}

8. Sensitivity Analysis
To simulate the performance of the developed IRI model, a random section was selected. IRI prediction values were generated for seven different years and compared with the observed IRI values. Figure 7 shows the observed vs. predicted plot of IRI for Section 01-0604 in Alabama. Predicted values were close to observed values. The predicted mean IRI\textsubscript{Mean} (1.23) is 10.2% lower than the observed IRI\textsubscript{Mean} (1.37). The projected values showed the roughness model behavior was captured by the developed model and the results were accurate and reliable for this section.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure7.png}
\caption{Observed and Predicted Plot of IRI\textsubscript{Mean} for Section 01-0604}
\end{figure}

Another sensitivity analysis was generated to evaluate future predictions using the developed model. The prediction was performed over 10 years from the last measurement. The variable that controls the time factor is the input variable “age”. For the predicted years, previous years’ climatological variables were averaged to be used. The ESAL values for the upcoming years were calculated by assuming an annual growth rate of 1%. No M&R intervention was assumed for this section. The model was able to predict future IRI\textsubscript{Mean} values successfully for Section 01-0604. As the road deteriorates over time, the IRI\textsubscript{Mean} value will increase without any M&R action. Accordingly, the sensitivity analysis results shown in Figure 8 presents promising predictions for this section.
Figure 8. ANN Future Prediction IRIMean for Asphalt Overlay on Concrete Section 01-0604

The observed IRIMean values start on the pavement age of 32 years and continue until 40 years. The ANN model was used to predict IRIMean values from 41 to 50 years. As expected, the predicted IRIMean values increase with time and an M&R intervention needs to be performed to maintain the ride quality and road safety for the users. The developed model can be used to identify in which year the section will need an intervention. Also, if no M&R is performed, the deterioration of the pavement occurs exponentially as can be seen from the slope of the IRIMean prediction curve after the pavement age of 43 years. For section 01-0604 an M&R intervention is recommended before the pavement age of 46 years to maintain an acceptable roughness value for the pavement. Therefore, the sensitivity analysis shows that the developed model can be used as a powerful tool by visualizing effective solutions for the future condition of the roads and their M&R planning.

9. Conclusions

In this paper, an artificial neural network approach with a backpropagation learning algorithm was utilized to develop IRI prediction models for asphalt overlay on concrete pavements. The best performing ANN model was selected based on the accuracy measures shown in Table 2. Model 5 showed better prediction accuracy for IRI values compared to the other ANN models developed. However, all the developed models are acceptable and can be used for generating reliable predictions. The developed ANN models have efficiently characterized the roughness phenomena on composite pavements. Most of the studies in the literature developed roughness models for asphalt or concrete pavements. This paper can be considered as a unique study that composite pavement roughness models were developed using ANNs approach in the LTPP database. Since asphalt overlay on concrete pavements is a large part of the LTPP database, this study can be employed by the transportation agencies and stakeholders. Therefore, the developed ANN model can be used as a prediction tool for IRI values and guide decision-makers to develop a better M&R plan. Furthermore, the developed model will predict future IRI values without the need for distress data. This will allow local and state agencies to save time from data collection and processing, resulting in cost reductions by providing a tool for better condition assessment and effective M&R scheduling.

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