International Roughness Index Modeling For Jointed Plain Concrete Pavement Using Artificial Neural Network

Salma Sultana¹, Hakan Yasar, Waheed Uddin, Rulian Barros

¹The University of Mississippi, Department of Civil Engineering, University, MS 38677 USA

ssultana@go.olemiss.edu

Abstract. Climate attributes such as precipitation, extreme temperature, and freeze-thaw cycles along with traffic loads cause pavement distresses. The maintenance need for pavements is decided based on the pavement condition rating such as International Roughness Index (IRI). Generally, an IRI rating less than 2.68 m/km is acceptable, and a rating greater than 2.68 m/km is considered unacceptable and classified as “very poor” condition of the pavement. It is imperative to be able to accurately predict pavement conditions to prepare proper Maintenance and Rehabilitation (M&R) programs for the pavements. This study aims to develop IRI models that can successfully estimate the IRI values for Jointed Plain Concrete Pavement (JPCP) considering the M&R history of the pavements using Artificial Neural Networks (ANNs) approach. The study was carried out with the database collected from Long Term Pavement Performance (LTPP) program. The variables used for the ANN model development are initial IRI, pavement age, concrete pavement thickness, equivalent single axle load (ESAL), climatic region (wet-freeze, wet non-freeze, dry-freeze, dry non-freeze), construction number (CN), and several climatological data. After utilizing various ANN model structures, the best performing ANN model resulted in promising statistical measures (i.e. $R^2 = 0.87$). The IRI prediction model can successfully estimate the increase of IRI values with the increase of ESAL value over time. The IRI prediction model can also estimate the decrease of IRI value after maintenance and rehabilitation. The predicted IRI values with good accuracy will help the local and state agencies to prepare for M&R programs for JPCP pavements and allocate a projected budget accordingly.

1. Introduction

An efficient and safe road network secures the nation’s economy and prosperity by providing public mobility and freight transport. One of the largest public infrastructure assets of a country is the road network. Well-maintained road networks are essential for appropriate response in emergencies. Timely maintenance and rehabilitation is one of the important factors to ensure the road networks in acceptable condition for the long term. The maintenance need for pavements is decided based on the present condition. There are several performance scales available such as Present Serviceability Rating (PSR), Present Serviceability Index (PSI), and International Roughness Index (IRI) to access the current condition of the pavement [1]. IRI measures the longitudinal profile of pavement, and the measurement is expressed in a single average number in a unit of in/mile or m/km. A higher IRI number indicates a rough pavement profile and a lower number indicates a smooth pavement profile. IRI provides an overall condition of pavement surfaces due to distresses, and for this reason, IRI is the internationally recognized pavement conditioning rating system. The pavement profile is measured...
using high-speed vans equipped with lasers, accelerometers, and computers to measure IRI. The highly equipped vans can measure the surface profiles at traffic speeds. The onboard accelerometer gives the necessary data to the computer to calculate changes in the vertical position of the vehicle body as the vehicle moves along the pavement, the laser measures the distance between the vehicle body and the roadway surface. Collected data is stored in the computer at regular intervals. The IRI value increases due to a decrease in pavement smoothness caused by distresses, which are induced by climatic and traffic attributes [1]. Generally, an IRI rating less than 2.68 m/km is acceptable and a rating above 2.68 m/km is considered unacceptable and a very poor condition rating [1].

Relatively few studies have been conducted in recent years to predict the roughness of concrete pavements. Oh et al. [2] analyzed the long-term performance of Jointed Plain Concrete Pavement (JPCP) in line with changes in standard mix design using evaluation of concrete properties based on Korea HPMS (highway pavement management system) and Korea LTPP data accumulated for over 15 years. The study found that the concrete pavements built in the 2010s by the specification of a durability-based mix design adopted in 2010 performed better with much fewer surface distresses than the concrete pavements built before 2010 using the specification of classical strength-based mix design. Naguib et al. [3] developed a regression model for IRI prediction for JPCP was developed based on data from the LTPP Project. A total of 327 data points from 81 pavement sections distributed all over the U.S. were used for model development. The model predicts IRI as a function of pavement age, initial IRI, faulting, number of spalled joints, number of transverse cracks, precipitation, and freezing index. The goodness of fit statistics of the model shows excellent improvement over the model implemented within the MEPDG. The model has a high coefficient of determination (R²) of 0.80. In addition, the bias in the predicted values of IRI was significantly lower compared to the MEPDG regression model. Hossain et al. [4] developed a prediction model for IRI for rigid pavement using climate and traffic data by employing Artificial Neural Network (ANN) modeling. The climate and traffic data are collected from the LTPP database. The ANN model is trained using 70% of climate, traffic, and IRI data, 15% data is used to test the model, and the rest 15% data is employed to validate the model. The trained model and the validated model are compared by calculating the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of ANN predicted IRI and measured IRI. The study developed a model for rigid pavement located at the wet no-freeze climatic zone, employing 7-9-9-1 ANN structure and using hyperbolic tangent sigmoidal transfer function, the RMSE value and MAPE value generated is 0.01 and 0.01 (1% error) respectively.

The previous literature review and discussion show that it is imperative to maintain acceptable road conditions over time. This goal is possible if the enhanced prediction models for pavement condition deterioration are used for pavement structural design and asset management. The literature review to date indicates that the Maintenance and Rehabilitation (M&R) history was not considered in the concrete pavement performance model. In the LTPP database, the M&R sequence is denoted by the construction number (CN). In the LTPP study, a test section on the road network was assigned CN1 when it was opened to the traffic. When the first M&R treatment was conducted, the construction number changed to CN2. The CN values increase as a result of more frequent M&R treatments. Generally, the M&R treatment intervention improves the pavement condition. On the JPCP highway, M&R treatment intervention improves the pavement condition with respect to longitudinal roughness, cracking, faulting, joint deterioration, and other surface defects. In the model development process, it is imperative to consider the CN intervention factor for realistic modeling of pre- and post-M&R practice. Recently, Mohamed Jaafar [5] developed mechanistic-empirical models for predicting IRI using the CN categorical variable included in the LTPP database. Therefore, this study considered CN for developing performance models of concrete pavements. The independent variables, used in the previous discussion are mostly distress, age, and environmental data. However, for future prediction of IRI, these distresses need to be predicted as well. The purpose of the research is to develop pavement performance (IRI) models employing ANN modeling technique for JPCP highway sections using the
LTPP database for all climatic zones. The goal is to develop IRI models that include pavement M&R history, traffic, and climate data.

2. Model development

2.1. Methodology

IRI is an important measure for estimating future conditions, timely maintenance, and/or major rehabilitation actions, as well as associated budget. Pavement performance (condition attributes of IRI) models can evaluate the deterioration process of pavement conditions, identify the major load and environmental attributes which affect the service life, provide forecasts over time, and play an essential role in the pavement asset management system. The model development process include literature review of past research studies, assembling databases for JPCP model development from the LTPP database, evaluation of the quality of databases, and development of pavement performance models using ANN.

2.2. Data Collection from LTPP Database for JPCP Highway Sections

The LTPP program was established to monitor and collect pavement performance data during 1987-1991 under the Strategic Highway Research Program (SHRP) of the National Academy of Science [6]. Since 1992, the Federal Highway Administration (FHWA) has continued the management and funding of the program [7]. The LTPP program has two vital classes of studies and several other smaller studies to investigate specific pavement-related details that are critical to pavement performance. The vital classes of study are the General Pavement Study (GPS) and the Specific Pavement Studies (SPS). The combined GPS and SPS programs involve over 2,500 test sections located on in-service highways throughout the United States and Canada. The LTPP program monitors and collects pavement performance data on all active sites. The collected data include information in seven modules: Inventory, Maintenance, Monitoring (Deflection, Distress, and Profile), Rehabilitation, Materials Testing, Traffic, and Climatic.

The LTPP data is collected at different spatial locations that exhibit values that are different across the LTPP regions. The following LTPP climate zone classification map (figure 1) was created during the initial recruitment phases of the LTPP test sections [5, 8], which indicates spatial and temporal variability that applied to the collected pavement attributes. Four different climate zones were identified namely wet-freeze, wet-nonfreeze, dry-freeze, and dry-nonfreeze zones. In certain areas, the regional contractors altered this map to state boundaries to ease data collection processes.

![LTPP Climate Zones](image)

Figure 1. LTPP climate zones [5]
The data were collected from the LTPP database of JPCP, which is GPS-3. A total of 107 GPS-3 JPCP pavement sections are included in LTPP that are located throughout the United States [9]. The IRI measurements are from 1989 to 2018. A total of 7,982 measurements are for 107 sections. By averaging the IRI value from one run, a database was created with 1,482 data points. The data used for the model included 590 data points of 43 JPCP sections from all over the United States. IRI measurements included measured left (inside) wheel path and right (outside) wheel path. The mean IRI is calculated by averaging IRI right (outside) and left (inside) wheel path measurements. Figure 2 shows the mean IRI of 43 JPCP pavement sections.

![Mean IRI Measurement](image)

**Figure 2.** Mean IRI distribution over the years

3. **ANN Models**

3.1. **Overview of ANN**

Artificial Neural Networks, (ANNs), is a powerful computational tool, in which highly interconnected processing neurons work together to investigate and solve a complex problem in a non-traditional manner [10]. The unique power of ANNs, which emulate the biological nervous system, lies in the tremendous number of interconnections between their neurons or processing elements because they provide significant advantages by learning from examples, producing meaningful and cost-effective solutions to numerous problems [10]. ANNs adapt themselves to changing circumstances and process information quickly to come up with desired outputs [10]. ANNs store data among the individual neurons of the network and process data in a parallel and distributed manner. ANN consists of three building blocks (a) input neurons or processing elements, representing the input for the problem, (b) connecting links known as axons, which connect input and output neurons and represent the connection weights that associate the input with the output, and (c) output neurons, or processing elements representing the output for the problem [4]. The architecture of a typical ANN consists of some hidden nodes that are usually arranged in layers such as an input layer, hidden layers, and an output layer. These layers are described as follows:

- **Input Layer:** This layer consists of independent variables used in the model.
- **Hidden Layer(s):** This layer consists of hidden nodes. The hidden layer can be one or more and each hidden layer can contain different numbers of hidden nodes.
- **Output Layer:** This layer consists of a dependent variable used in the model.

3.2. **ANN Methodology**

The development of the ANN model includes four sequential stages. The ANN architecture is determined based on parameter characteristics and ANN knowledge in the first stage. In this step, the
datasets are divided into three different sub-datasets: training, testing, and validation. In Yaserer’s study, the network was trained and tested, in the second stage using the optimum number of hidden nodes and iteration, attained from the first stage [11]. The best performing network obtained from the second stage was validated using validation sub-datasets in the third stage. The best performing network attained from the second stage was retrained using all the data, in the fourth stage [11]. Normally, retraining the network with all experimental data is expected to provide reliable predictions and overall better accuracy measures. However, it has been shown through several research studies [11-14] that stage four is recommended to arrive at a better-performing network model. In this research the development of ANN models were carried out using the ANN TRSEQ1 computer program [13].

3.3. ANN Model Architecture

In the preliminary research, using the selected JPCP section of the LTPP database, several models were tried with varying numbers of independent and dependent variables (i.e., inputs and outputs). The first model had six input variables but CN was a categorical variable with two categories 0 for CN1 and 1 for any other CN number. The region was also assigned as a categorical variable with four categories. Therefore, the first model had 10 input and 2 output variables (i.e., IRI for inside and outside wheel path). The second model had the same number of input variables, but the dependent variable was mean IRI (MRI). The third model had 13 input variables (including 4 climatological variables) and one dependent variable (mean IRI). Table 1 shows the independent variables used in this study for the ANN model. The independent variables used in the MEPDG model are related to distresses, which need to be measured or predicted for future years, to predict IRI. On the other hand, the ANN model developed in this research used easily available independent variables.

| Table 1. Independent and Dependent Variables Used in ANN Model. |
|---------------------------------------------------------------|
| **Input Variables** | **Model 1** | **Model 2** | **Model 3** |
| IRI₀ (Initial IRI m/km) | Initial IRI Right Wheel Path, m/km | Initial Mean IRI, m/km | Initial Mean IRI, m/km |
| Age (Pavement age, years) | Age | Age | Age |
| h (Concrete pavement thickness, in) | h | h | h |
| ESAL (Equivalent Single Axel Load) | ESAL | ESAL | ESAL |
| Climatic Region (Categorical variable for LTPP climatic region) | Wet, Non-Freeze | Wet, Non-Freeze | Wet, Non-Freeze |
| | Dry, Non-Freeze | Dry, Non-Freeze | Dry, Non-Freeze |
| | Wet, Freeze | Wet, Freeze | | |
| | Dry, Freeze | Dry, Freeze | | |
| CN (Construction Number, Categorical variable for M & R) | No Intervention 0 | No Intervention 0 | No Intervention 0 |
| | Any Intervention 1 | Any Intervention 1 | Any Intervention 1 |
| Climatological Inputs | Mean Annual Temperature (°C) | Total Annual Precipitation (in) | Freezing Index Year |
| | Freeze-Thaw (days) | | |
| **Output Variables** | | | |
| IRI Right Wheel Path, m/km | Mean IRI, m/km | Mean IRI, m/km |
3.4. ANN Model Selection

Three best performing networks from each model (Model 1, Model 2, and Model 3) were selected based on statistical measures such as minimum values of Mean Absolute Relative Error (MARE), Averaged-Squared-Error (ASE), and maximum values of Coefficient of Determination (R²). A total of 590 datasets were used to build the desired database; 302, 144, and 144 subdatabases were used, respectively, for training, testing, and validation purposes. Datasets that include minimum and maximum values of each variable were included in the training phase for the network to represent the characteristics of the response. The maximum and minimum ranges of each input/output variable for ANN model development were chosen on purpose to be wider than their actual ranges for better mathematical mapping (30). The statistical measures of the best performing network for Model 1, Model 2, and Model 3 are shown in Table 2. With the lowest ASE value of 0.001766 and the highest R² value of 0.87169 in all data stage, Model 2 was selected to be the best performing model.

| Dataset    | Statistical Error Measures | Model 1 (6-20000) | Model 2 (6-9-20000) | Model 3 (3-5-20000) |
|------------|---------------------------|--------------------|--------------------|--------------------|
|            | MARE | 15.745 | 10.668 | 12.693 |
| Training   | R²   | 0.76194 | 0.85476 | 0.8527 |
|            | ASE  | 0.003375 | 0.002127 | 0.00217 |
| Testing    | MARE | 13.934 | 13.096 | 13.516 |
|            | R²   | 0.65816 | 0.79938 | 0.7513 |
|            | ASE  | 0.004032 | 0.002644 | 0.003282 |
| Validation | MARE | 15.327 | 14.465 | 15.292 |
|            | R²   | 0.7403 | 0.7413 | 0.74104 |
|            | ASE  | 0.002882 | 0.003545 | 0.00403 |
| All Data   | MARE | 12.98 | 10.437 | 11.822 |
|            | R²   | 0.80226 | 0.87169 | 0.85598 |
|            | ASE  | 0.002526 | 0.001766 | 0.001986 |
| Final Network Structure | 10-6-2 | 9-9-1 | 13-5-1 |

3.5. ANN Model Results

Model 2 was chosen as the best performing network based on statistical measures (ASE, MARE, and R² value) of all data. The final model structure has 9 inputs of independent variables, 9 hidden nodes, and 1 output (9-9-1) (figure 3).

Figure 3. Network architecture for best model (Model 2, Structure: 9-9-1)
Model 2 will be discussed further to explain the considerations made to choose the best model. The comparison of the prediction accuracy measures for ANN Model 2 is graphically presented in figure 4. From figure 4 it is evident that once observed IRI rises above 3.0, the model steadily underestimates the prediction output.

![Image of Mean IRI plot](image)

**Figure 4.** Observed mean IRI (m/km) vs. predicted mean IRI (m/km)

### 3.6 Sensitivity Analysis

The 590 data points are assigned section sequence numbers from 1 to 590. Figure 4 shows the observed and Model 2 predicted mean IRI values. From figure 5, it is demonstrated that the predicted IRI has apprehended most of the variability in the IRI observed values.

![Image of Observed and Predicted IRI](image)

**Figure 5.** Observed and predicted mean IRI (m/km) plot
Figure 6 shows the observed and predicted IRI for Section 06-3017, in California. The predicted values follow the observed values closely. The difference in the mean values of observed and predicted is -3.1%.

![Figure 6. Observed and Predicted mean IRI plot of JPCP section in California](image)

Randomly selected sections with different M&R types (CN1 and CN2) were used to generate IRI predictions for future years. For IRI predictions, the ESAL values were assumed with an annual growth rate of 1%. Figure 7 shows that the IRI prediction model follows the trend of the observed values. Additionally, it can estimate the increase of IRI values with time and decrease of IRI value after maintenance and rehabilitation.

![Figure 7. ANN future prediction plot of mean IRI for JPCP section in California](image)
4. Conclusions
The concluding remarks are summarized below:

(1) The best model to predict IRI was found to be Model 2 with an $R^2$ value of 0.87. The total data points used to develop the IRI prediction ANN model were 590. The developed ANN model in this study has relatively higher accuracy than the previously developed models via multiple regression and ANN models. The developed IRI prediction model can successfully characterize the behavior (i.e. the increase of IRI values with time and decrease of IRI value after maintenance and rehabilitation).

(2) The ANN model developed in this research used easily available independent variables. The developed model can predict the IRI values without using distress data that will help the local and state agencies to prepare M&R programs and budgets without estimating distresses in future years. The only variable needing to be estimated is ESAL data. The agency can use the historical traffic data for a particular pavement and project the future traffic data based on the annual traffic growth rate for the highway to provide this input.

(3) The best performing model (Model 2) does not need any climatological inputs to predict IRI for future years.

5. Recommendations
The recommendations for better model development are described below:

(1) In this study, ESAL was used as an independent variable. The cumulative ESAL (CESAL) should be used as an independent variable to incorporate the accumulated traffic load for better performance prediction.

(2) The developed IRI prediction models in this study used 590 data points. All data points should be used to develop models for better characterization.

(3) Further study on exploring M&R types and their classifications need to be done.

(4) A graphical user interface should be developed for agencies to utilize IRI prediction models and monitor pavement conditions.

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References
[1] Uddin, W., W.R. Hudson, Ralph Haas. Public Infrastructure Asset Management. McGraw-Hill, Inc., New York, 2013. ISBN 0071820116 ISBN-13: 978-0071820110.

[2] Oh, Han Jin, Jun Young Park, Hyung Bae Kim, Won Kyong Jung, and Jung Hun Lee. Performance Evaluation of JPCP with Changes of Pavement Mix Design Using Pavement Management Data. Advances in Civil Engineering. Volume 2019, Article ID 8763679, 10 Pages. https://doi.org/10.1155/2019/8763679.

[3] Naguib, Ahmed M., Sherif M. EL-Badwy, and Murad H. Ibrahim. International Roughness Index Predictive Model for Rigid Pavements based on LTPP Data. ResearchGate. 2019. https://www.researchgate.net/publication/330993303 Accessed 19 February 2020.

[4] Hossain, M., Gopisetti, L.S.P. & Miah, M.S. Artificial neural network modelling to predict international roughness index of rigid pavements. Int. J. Pavement Res. Technol. 13, 229–239 (2020). https://doi.org/10.1007/s42947-020-0178-x

[5] Mohamed Jaafar, Z. F. Computational Modeling and Simulations of Condition Deterioration to Enhance Asphalt Highway Pavement Design and Asset Management. Ph.D. Dissertation, Department of Civil Engineering, The University of Mississippi, Oxford, August 2019.
[6] FHWA. About Long-Term Pavement Performance. Federal Highway Administration (FHWA), Research and Technology, 20 January 2015. cms7.fhwa.dot.gov/research/long-term-infrastructure-performance/ltpp/long-term-pavement-performance Accessed 11 October 2019.

[7] FHWA. About Long-Term Pavement Performance. Federal Highway Administration (FHWA), Research and Technology, 20 January 2015. http://www.fhwa.dot.gov/research/tfhrc/programs/infrastructure/pavements/ltpp/ Accessed 25 February 2015.

[8] Pierce, L. M. and McGovern, G. NCHRP Synthesis 457, Implementation of the AASHTO Mechanistic Empirical Pavement Design Guide and Software - A Synthesis of Highway Practice. 2014.

[9] FHWA. Long Term Pavement Performance (LTPP) Info Pave: Data. LTPPInfoPaveTM. U.S. Department of Transportation Federal Highway Administration (FHWA). https://infopave.fhwa.dot.gov/Data/DataSelection Accessed 11 November 2019.

[10] Lin, J., J.-T. Yau, and L.H. Hsiao. Correlation analysis between international roughness index (IRI) and pavement distress by neural network. In Proc., 82nd Transportation Research Board Annual Meeting. Washington, DC. Transportation Research Board. 2003.

[11] Yasarer, H. I. Characterizing the Permeability of Concrete Mixes Used in Transportation Applications: A Neuronet Approach, Master’s Thesis, Kansas State University, Manhattan, KS, 2010. 105 pp.

[12] Najjar, Y. M. and Mrayan, S. “ANN-Based Profiling: Data Importance,” Intelligent Engineering Systems through Artificial Neural Networks, Vol. 19, pp. 155-162.

[13] Najjar Y. Quick Manual for the Use of ANN program TRSEQ1. Department of Civil Engineering, Kansas State University, Manhattan, Kansas, USA. 1999.

[14] Yasarer, H. and Najjar, Y. Development of a Mix-Design Based Rapid Chloride Permeability Assessment Model Using Neuronets. Proceedings of International Joint Conference on Neural Networks, San Jose, California, USA, July 31 – August 5, 2011.