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Prediction of pavement roughness using a hybrid gene expression programming-neural network technique

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ABSTRACT

Effective prediction of pavement performance is essential for transportation agencies to appropriately strategize maintenance, rehabilitation, and reconstruction of roads. One of the primary performance indicators is the international roughness index (IRI) which represents the pavement roughness. Correlating the pavement roughness to other performance measures has been under continuous development in the past decade. However, the drawback of existing correlations is that most of them are not practical yet reliable for prediction of roughness. In this study a novel approach was developed to predict the IRI, utilizing two data sets extracted from long term pavement performance (LTPP) database. The proposed methodology included the application of a hybrid technique which combines the gene expression programming (GEP) and artificial neural network (ANN). The developed algorithm showed reasonable performance for prediction of IRI using traffic parameters and structural properties of pavement. Furthermore, estimation of present IRI from historical data was evaluated through another set of LTPP data. The second prediction model also depicted a reasonable performance power. Further extension of the proposed models including different pavement types, traffic and environmental conditions would be desirable in future studies.

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1. Introduction

Performance indicators are widely used to evaluate pavement condition and serviceability. Most notably, parameters such as the Present Serviceability Index (PSI), Pavement Condition Index (PCI), and IRI are commonly used in performance

assessment. IRI, in particular, is a primary performance measure that is often employed by highway agencies to predict pavement performance. The present study aims at employing LTPP data for the development of IRI prediction modeling through the use of a hybrid GEP-ANN technique.

The IRI is a World Bank sponsored performance indicator that was developed during the International Road Roughness

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Experiment (IRRE) in 1982. The IRI was conceived to provide a common global measurement for pavement roughness comparison. The IRI of a pavement is defined as the average rectified slope (accumulated suspension motion to distance traveled) as derived from a mathematical model of a standard quarter car passing over a measured profile at a speed of 50 mph (Ozbay and Laub, 2001). The roughness or smoothness of the pavement is a comprehensive assessment indicator that takes into account not only both ride quality and comfort of the pavement, but also serving as an indicator of the presence of collective distresses. As the pavement ages, the roughness or IRI of the pavement increases, representing deterioration. IRI is a primary mode of assessing pavement condition, as Wang et al. (2007) stated, and one of the main functional performance indicators used by the Mechanistic-Empirical Pavement Design Guide (MEPDG).

The health state of the pavement can be evaluated by closely observing the type and amount of present distresses, examining the material properties of the pavement structure, and estimating the construction quality. Unfortunately, this particular method of evaluation is neither practical nor cost-effective for both project and network level analysis of pavements. Therefore, models have been developed to forecast pavement performance using performance measures, such as IRI. Various methods of IRI prediction modeling have been practiced in the literature. Given the variable characteristics of pavement structures and data collection methods, it is understood that no single model can be successfully applied to all pavements. The structure of prediction model is dependent on the type and amount of historical performance data available.

Current MEPDG-IRI prediction models are actually a by-product of traditional regression statistical analysis (Wang et al., 2007). It is a function of traffic, material, geometric and climatic conditions derived from the LTPP database (Schram and Abdelrahman, 2006). There are some discussions that IRI prediction modeling through regression analysis may not be the ideal method, given the complex relationships between the model variables and actual pavement performance. Choi et al. (2004) discussed that the relationships between material, construction variables and pavement performance measures were too complex and poorly understood to be explained by traditional statistical methods.

Apart from traditional regression analysis, other techniques have been employed for pavement performance modeling. One example is the use of gray theory for IRI prediction. Jiang and Li (2005) employed LTPP datasets to perform a comparison between gray relational models and the MEPDG regression models. They found that in different cases, gray relational models offered better IRI predictions, while utilizing less distress parameters than the MEPDG counterpart. The use of artificial neural networks for modeling infrastructure deterioration is being popular and various studies have been performed to assess their effectiveness. A roughness prediction study by Attoh-Okine (1994) remarked that employing ANN roughness prediction models were feasible and could be the basis for developing a generic intelligent pavement deterioration process. Later, Attoh-Okine et al. (2003) developed a method for

pavement roughness prediction using multivariate adaptive regression splines (MARS) which allowed finding the relative significance of pavement condition, traffic and environmental parameters. Kargah-Ostadi et al. (2010) developed an ANN-based pattern-recognition model to predict IRI for flexible pavement rehabilitation sections in a wet-freeze climate using LTPP database.

The World Bank has developed a roughness prediction model through the Highway Development and Management (HDM) program in which five factors contributed the most: cracking, rutting, potholes, environmental conditions and structural deterioration (Odoki and Kerali, 2000).

Von Quintus and Killingsworth (1997) conducted a study on LTPP data to find relationships between deflection time-history data and pavement conditions such as IRI. Rada et al. (2012) contained a comprehensive review of IRI prediction models while trying to correlate ride quality and structural adequacy of pavement structures using LTPP database. Stubstad et al. (2012) developed a stochastic approach for understanding and assessing deflection data for network-level pavement management systems (PMS) including IRI models.

The focus of this study is to couple genetic programming and artificial neural network for IRI prediction on a dataset collected from the LTPP database. The first part of this study includes developing a hybrid approach for prediction of IRI from pavement structure and traffic parameters. Thereafter, historical roughness data along with the traffic and structural conditions are employed to predict the roughness.

2. Methodology and database

The LTPP program was initiated as a part of the Strategic Highway Research Project (SHRP) in 1987 and was expanded to a twenty-year program under the coordination of the Federal Highway Administration (FHWA). The main objectives of this program are to improve and develop a designed process for new and rehabilitated pavements, evaluate existing pavement conditions, develop methodologies for improving existing design and maintenance processes, and determine the effect of the construction processes, environmental criteria, traffic and the materials properties on the structural performance of flexible and concrete pavements (Elkins et al., 2003).

The LTPP information management system (IMS) is a comprehensive pavement management database documenting historical performance data for over 2500 in-service and monitored test sections spanning across North America. Different types of information are stored within the database in the form of seven modules: inventory, maintenance, monitoring, rehabilitation, material testing, traffic, and climatic data. The datasets collected for this study was extracted from the LTPP data documented for states of Indiana, Iowa, Maryland, New Jersey, New York, Tennessee, Arkansas, and Oklahoma in the United States, New Brunswick and Prince Edward Island in Canada. From the extracted data, those sections with asphalt concrete over unbound granular layers were selected to analyze. Such database was extracted from the study performed by Ozbay and Laub (2001).

Table 1 – Descriptive statistics of first set of LTPP data.

	Variable	Minimum	Maximum	Average	Median	Standard deviation	Range
Predictor	AGE (1000 d)	0.89	16.50	4.41	3.98	3.05	15.62
	ESAL (millions)	0.15	19.50	3.10	0.98	5.21	19.35
	SN	3.23	7.22	4.92	4.60	1.17	3.99
Dependent	IRI (m/km)	0.71	2.80	1.34	1.27	0.47	2.09

Various material, structural and traffic parameters, affecting the deterioration of a pavement structure, can be assessed through observation of the IRI over time. Material properties such as asphalt content, gradation type, and percent fines can affect the progression of IRI. Other factors that can be related to the deterioration of the road include: traffic loading in terms of equivalent single axle loads (ESALs), age, and the structural number (SN) of the pavement. Since all these parameters affect the deterioration of the pavement, it would be reasonable to utilize them as input variables for performance prediction modeling. Even though, [Perera et al. \(1998\)](#) suggested that the IRI prediction models, which relied on material properties, would contain many variables, might be complex and less reliable. It seemed that utilizing parameters such as ESALs, age, and SN would yield more practical and dependable results to predict the performance of pavements in terms of IRI ([Ozbay and Laub, 2001](#); [Terzi, 2013](#)).

The reliability of IRI prediction models are dependent of the material behavior, loading and environmental conditions. Therefore, it would be reasonable to consider the historical IRI data along with the structural characteristics to improve the model efficiency. In this study, two sets of LTPP data were employed to develop prediction models. The first dataset consists of the collected IRI data along with the SN, age and cumulative ESALs. The descriptive statistics of the variables in the first database are summarized in [Table 1](#).

The second dataset contained initially measured IRI (IRI_0), initial age (AGE_0), initial cumulative ESAL ($ESAL_0$), SN, difference in age (ΔAGE), and difference in cumulative ESALs ($\Delta ESAL$). The descriptive statistics of the second dataset are summarized in [Table 2](#).

To develop a reliable prediction model, various considerations must be taken into account. One is that a significant amount of IRI, distress, and deflection data in LTPP database are recorded at different times. The time difference among collected data may have an impact on the prediction of ultimate pavement deterioration. Another consideration is that IRI values collected from profilometers and other data

acquisition methods can vary along the span of the road depending on the exact longitudinal direction.

The following section includes the process of model development using the extracted datasets from LTPP.

3. Development of prediction models and results

A combination of GEP and ANN methods was employed to develop the first prediction model. As discussed earlier, the development of pavement roughness prediction model in this study included two major steps. The first step consisted of predicting the initial IRI using the LTPP documented age, structural number and cumulative ESALs. The second model development process included the implementation of a robust methodology to collectively predict the present value of pavement roughness using the historical data such as IRI_0 , AGE_0 , $ESAL_0$ (cumulative), ΔAGE , and $\Delta ESAL$ (Δ indicates the difference between measured parameter from time of initial IRI documentation to the latest).

Soft computing techniques have been employed in several transportation and pavement related problems during the past decade. Examples of such applications in solving complex nonlinear problems could be found in [Alavi et al. \(2011\)](#), [Gandomi et al. \(2010\)](#), [Mazari and Niazi \(2015\)](#), [Reddy et al. \(2004\)](#), [Shahnazari et al. \(2012\)](#), and [Sun et al. \(2007\)](#). ANN and fuzzy logic algorithms have been employed to predict the roughness index as documented in [Choi et al. \(2004\)](#), [Terzi \(2013\)](#), and [Ozbay and Laub \(2001\)](#). The drawback of such methods is that the final product is not in the form of mathematical equations that can be easily implemented.

ANNs consist of mathematical models inspired by simulation of biological nervous systems. Such algorithms could be implemented in solving complex nonlinear models and mostly supervised learning problems. One of the most popular neural networks is the multi-layer perceptron (MLP). MLP includes an input layer (which consists of independent variables), a hidden layer (a number of hidden variables also

Table 2 – Descriptive statistics of second set of LTPP data.

	Variable	Minimum	Maximum	Average	Median	Standard deviation	Range
Predictor	IRI_0 (m/km)	0.59	2.92	1.35	1.28	0.53	2.33
	AGE_0 (d)	1086	16,503	4449	4047	2910	15,417
	$ESAL_0$ (millions)	0.19	19.49	2.92	1.04	4.89	19.30
	SN	2.85	7.22	4.75	4.57	1.17	4.37
	ΔAGE (d)	0.27	2.89	1.19	0.99	0.53	2.62
	$\Delta ESAL$ (millions)	0.08	19.23	2.72	1.64	3.52	19.15
Dependent	IRI_p (m/km)	0.59	3.14	1.43	1.35	0.58	2.55

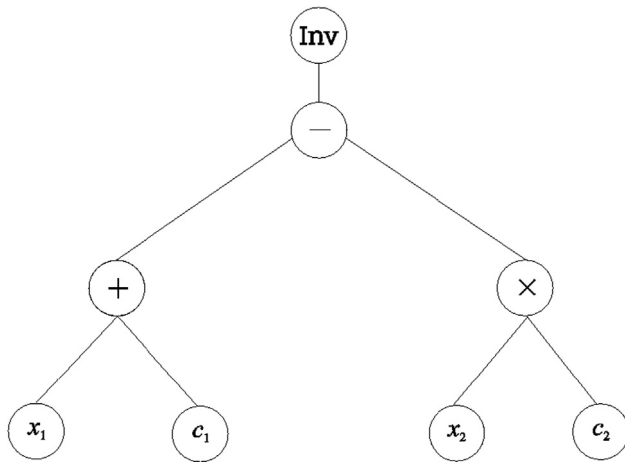


Fig. 1 – Representation of an expression tree in gene-expression programming. (Inv represents the inverse function).

known as hidden neurons) and an output layer which contains the target values. These variables are interconnected with several weighted links. The best solution of the network is found by forward feeding the initial solutions, back-propagating the errors throughout the entire network and adjusting the connection weights (Hertz et al., 1991).

Adaptive neuro-fuzzy inference system (ANFIS) is a Sugeno-type fuzzy inference system which also incorporates the principles of neural networks (Sugeno, 1985). Fuzzy inference process consists of modeling a set of outputs from a selected number of inputs utilizing specific membership functions, logical operations and if-then rules (Zadeh, 1965). In fuzzy logic, any statement is not completely true or false and there is always a percentage of truth or falseness. The drawback of ANFIS models is the complexity associated with the membership functions and if-then rules which comprise the final model.

Gene expression programming was introduced as a method to produce a practical solution for prediction models (Ferreira, 2001). GEP is a specialized form of genetic programming (GP) which can be referred to as a type of genetic algorithms since it is essentially composed of a population of mathematical solutions that ultimately

evolves the selection of the best solution using an optimization process. In a GP, which was first introduced by Koza (1990), the individuals in the genetic algorithm are computer programs. GP evolves these computer programs through expression trees utilizing a fitness criterion. The GEP technique starts with selecting a function set (consisting of mathematical and logical operations) and a terminal set. It then loads the dataset to the entire model to evaluate the fitness function and create an initial random population of chromosomes (i.e. computer programs). For each individual computer program, expression trees are created in order to execute the program and evaluate the fitness criteria. Selected programs are then replaced with the initial population. This process would be rewinded for a specific number of generations or until reaching the selection of best solution (Ferreira, 2001).

An example of defining an algebraic equation with an expression tree is demonstrated in Fig. 1. In this figure, the head and intermediate nodes represent mathematical functions. The tail nodes symbolize independent variables or constant values. Such nodes are interconnected with the links to build an algebraic expression. The mathematical form of expression tree in Fig. 1 is as follows

$$\frac{1}{x_1 + c_1 - x_2 c_2} \tag{1}$$

where x_1 and x_2 are the independent variables, c_1 and c_2 are the constants.

The transition between the expression trees and algebraic equations is performed in the form of symbolic regression to fit a nonlinear function to a set of data. The evolution of the programs toward the best solution is controlled by a fitness function. An appropriate fitness function is the root mean squared error (RMSE), which is defined in the form of Eq. (2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} \tag{2}$$

where x_i is the measured value, y_i is the predicted value, and n is the number of observations.

If the desired fitness criterion is not met, the reproduction and modification process will be initialized. This process includes: replication, mutation (change of functions and variables in head and tail nodes), transposition and insertion, and

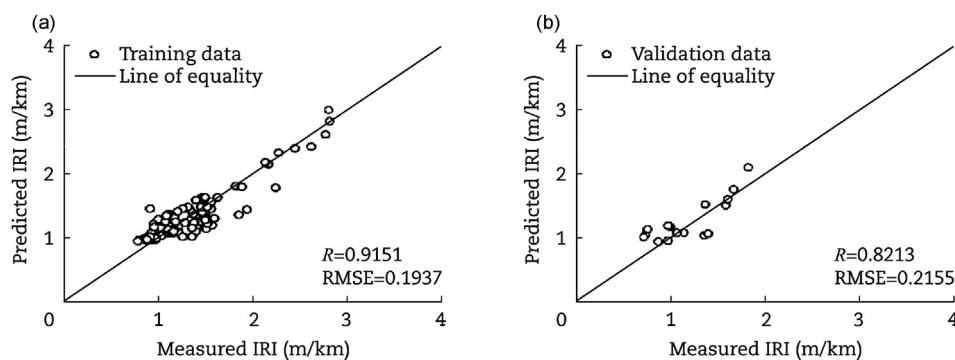


Fig. 2 – Comparison of predicted and measured IRI values for training and validation data. (a) Performance of GEP model for training data. (b) Performance of GEP model for validation data.

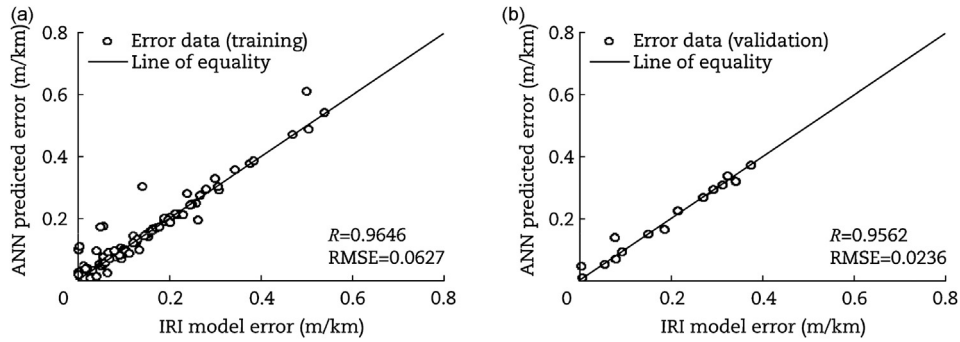


Fig. 3 – Performance of ANN predicted errors from GEP model. (a) Performance of ANN model for training data. (b) Performance of ANN model for validation data.

recombination (Ferreira, 2001). The best GEP solution is eventually validated through the use of an independent set of data which was not introduced during training phase. The following sections contain the process of developing IRI prediction models based on extracted LTPP data in this study.

The general form of the mathematical model proposed for the first set of LTPP data is as following

$$IRI = f(SN, AGE, ESAL) \tag{3}$$

where IRI is the estimated international roughness index (m/km), SN is the structural number, AGE is the time for construction of the pavement (1000 d), ESAL is the cumulative equivalent single axle loads (millions).

Both Ozbay and Laub (2001) and Terzi (2013) indicated that using the SN, age, and ESALs of the respective case studies for developing the IRI prediction model would yield a better correlation between predicted and measured roughness indices. As a result, three independent variables (SN, AGE and ESAL) were employed to develop the GEP model in this study.

To build the GEP structure and find the best prediction model, the GeneXproTools[®] software package was utilized in this study. The first database consisted of ninety-five records, from which, eighty records were selected to train the GEP model. Fifteen independent data records were then used to validate the developed model. The GEP algorithm consisted of

thirty chromosomes, with a head size and gene number of eight and three, respectively. It should be mentioned, that the selection of these parameters would impact the generalization of the proposed model. An iterative process selects the optimized parameters that would be employed in the GEP model. The RMSE parameter was selected as the fitness function. To further evaluate the performance of the developed model, the correlation coefficient (R) was calculated for both training and validation data sets. The result of the best GEP solution is in the form of Eq. (4).

$$IRI = 0.974 + 2.497ESAL + 0.0768ESAL \cdot SN_2 + 0.009AGE_2 \cdot ESAL - 0.889ESAL \cdot SN - 0.0025AGE \cdot ESAL_2 \tag{4}$$

Fig. 2 illustrates the GEP-predicted roughness values compared to the measured IRIs from the LTPP database. Even though the training dataset shows a reliable correlation coefficient, the validation data exhibits relatively less correlation between the predicted and measured IRIs. To further improve the results of the GEP model, a hybrid approach was employed. A dataset of error values (defined as the difference between predicted IRI from the developed GEP model and measured IRI) was created. This dataset was selected as the target values for an ANN model. Similar to the GEP process, the input parameters for the ANN model were SN, AGE, and cumulative ESALs. The ANN model was comprised of an input layer including the predictor variables, a hidden layer with twenty hidden neurons and an output layer containing error values as the targets. The multilayer feed-forward neural network model with back-propagation of errors was employed in this phase of study. Levenberg–Marquardt algorithm was selected to train the ANN model. Two types of transfer functions were utilized for preparation of the data: log-sigmoid function for pre-

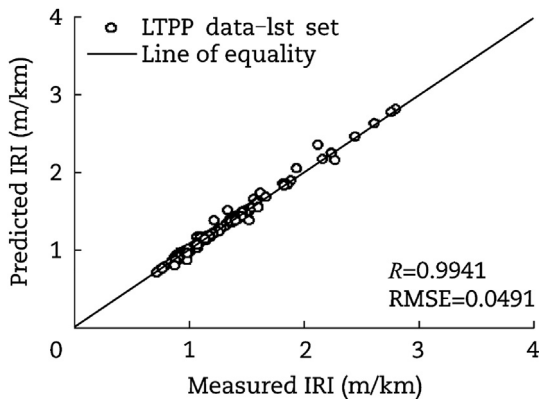


Fig. 4 – Performance of hybrid GEP-ANN model for IRI prediction.

Table 3 – Comparison of various prediction models for IRI from LTPP data.

IRI model	Correlation coefficient (R)
ANN (Ozbay and Laub, 2001)	0.9251
ANFIS (Terzi, 2013)	0.9862
GEP (current study)	0.9053
GEP-ANN (current study)	0.9941

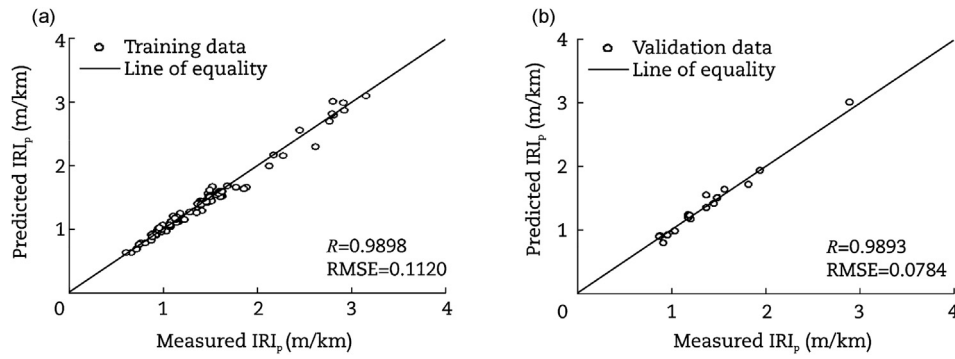


Fig. 5 – Comparison of predicted and measured IRI_p for training and validation data for the second LTPP data set. (a) Performance of prediction model for training data. (b) Performance of prediction model for validation data.

processing and linear function for post-processing. Fig. 3 shows the prediction power of ANN model. The error values predicted from ANN model were then introduced to the GEP model. The performance of the final hybrid prediction model is shown in Fig. 4. The hybrid GEP-ANN approach seemed to be effective as an IRI prediction model when compared to the initial GEP model. This is further supported by comparison of RMSEs for both approaches (GEP-ANN: 0.0491 m/km, GEP model: 0.2046 m/km).

A comparison between the developed hybrid GEP-ANN model with other IRI prediction models, in the literature, is included in Table 3. It should be reminded that for comparison purposes, all prediction models utilized the same variables for roughness prediction. The robustness of the developed hybrid model, compared to the ANN model and ANFIS is satisfactory owing to the fact that the developed models are in the form of algebraic equations (Ozbay and Laub, 2001; Terzi, 2013).

It is noteworthy that the generalization of the hybrid model depends on the range of the input variables used for the model development process. The LTPP data in this study were limited to specific pavement structures and traffic conditions. Including a wider range of input parameters will enhance the generalization of the IRI prediction model in the future studies.

For the second part of this study, a total of ninety-eight records were extracted from LTPP data. The present roughness (IRI_p) was the dependent variable while the IRI₀, AGE₀, ESAL₀, SN, ΔAGE, and ΔESAL were the predictors.

The proposed model is in the form of Eq. (5).

$$IRI_p = f(IRI_0, AGE_0, ESAL_0, SN, \Delta AGE, \Delta ESAL) \quad (5)$$

Eighty records from this dataset were randomly selected to train the GEP algorithm and the remaining data were used

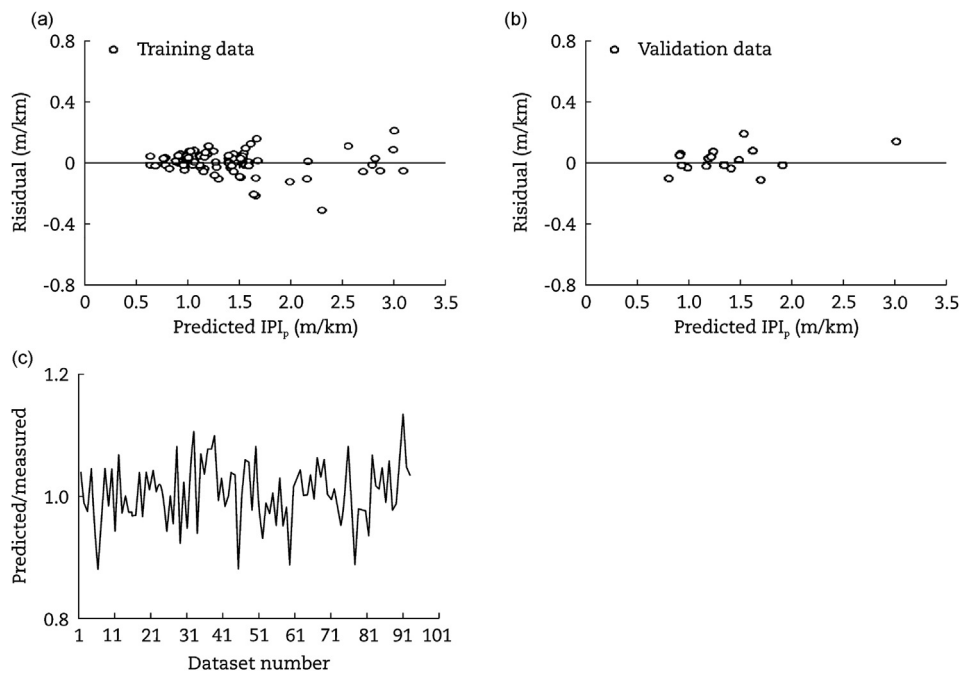


Fig. 6 – Residual plots and ratio of predicted to measured IRI_p. (a) Residual plot of training data for second model. (b) Residual plot of validation data for second model. (c) Predicted to measured ratios for the second prediction model.

to validate the model. The GEP model was developed using a set of forty chromosomes, with head size of ten and containing four genes. The RMSE indicator was selected as the fitness function to evaluate the performance of the evolved solutions.

Since the contribution of SN parameter in prediction of IRI_p was not significant, it was excluded from the final model. The final GEP solution is found to be in the form of Eq. (6).

$$IRI_p = (AGE_0 + \Delta ESAL + ESAL_0^2) \frac{IRI_0}{64.4 + AGE_0} + \left(4.09 - 2\Delta AGE - \frac{5.53}{IRI_0}\right)^{-1} + \left[\exp(\Delta AGE) - ESAL_0 - \frac{1}{IRI_0} - 13.85\right]^{-1} \quad (6)$$

A comparison of the GEP-predicted roughness values and actual IRI values (from the second data set) is illustrated in Fig. 5. The proposed GEP model shows a reliable prediction power ($R = 0.9912$ for validation data). The RMSE of the training and validation datasets are 0.1120 and 0.0784 m/km, respectively. Again, the generalization of the developed model is limited to the range of input data used in this study and could be further expanded to a wider range of roughness data in future studies.

Fig. 6 illustrates the residual plots of the predicted IRI values as well as the ratio of predicted/measured roughness values. Residuals of IRI prediction model are between -0.4 and 0.2 m/km for the training data used in this study. Such values for the validation dataset are less than ± 0.2 m/km. Furthermore, the ratio of predicted to measured roughness values are less than 15 percent as illustrated in Fig. 6(c).

4. Conclusions

In this study, two sets of pavement roughness data, extracted from the LTPP database, were utilized. The first set of data was used to develop a roughness prediction model using a gene-expression programming technique. The proposed model was then further improved by utilization of a hybrid GEP-ANN approach. The hybrid method was found to effectively predict the IRI. The performance of the proposed process deemed satisfactory compared to the similar prediction models found in the literature.

In the second part of this study, a GEP approach was employed to formulize the prediction of present IRI using an independent set of historical LTPP roughness data. The developed model was found to be a reasonable approach to predict roughness. Generalization of the proposed models in this study would be further improved using wider range of traffic data, pavement structural properties and roughness indices in future studies.

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