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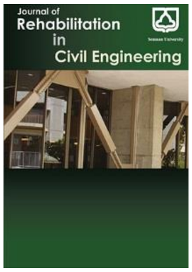

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Development of An Artificial Neural Network Model for Asphalt Pavement Deterioration Using LTPP Data

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ABSTRACT

Deterioration models are the essential parts of any Pavement Management System (PMS). These models are employed to predict future pavement situation based on existence condition, parameters causing deterioration and implications of various maintenance and rehabilitation policies on pavement. The majority of these models are in consonance with roughness which is one of the most important indices in pavement evaluation. High correlation between International Roughness Index (IRI) and user comfort led to modeling pavement deterioration based on IRI during PMS history. On the other hand, in recent years Artificial Neural Network (ANN) which is a valuable tool of soft computing is used in pavement modeling, broadly. This study assessed the development of an ANN pavement deterioration model based on IRI applying Back-Propagation Neural Networks (BPNN) technique. The Long-Term Pavement Performance (LTPP) data was extracted from two General Pavement Study (GPS) sections including GPS-1 and GPS-2. After training and testing the developed model, results were compared with a polynomial regression model. Results revealed that predicted IRI values with developed ANN model have a good correlation with measured values rather than the polynomial regression model for both GPS-1 and GPS-2 sections.

1. Introduction

Transportation network is an important part of economic development, while pavement is a principal infrastructure in the transportation network. These structures are directly in contact with vehicle load and transfer it to road subgrades to provide a safe and feasible bed for transportation of vehicles. Maintaining pavements from deterioration will preserve countries' national wealth besides improving transportation safety and

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comfort. It is crucial to predict pavement behavior during its lifecycle in order to provide rehabilitation before it reaches critical condition. This will decrease maintenance and rehabilitation costs besides providing a safe transportation network [1].

Development of reliable pavement deterioration prediction models is valuable for transportation policy makers and will lead to more economical highway management. Current strength of any Pavement Management System (PMS) depends upon the measurement of existing pavement conditions rather than predicting future conditions. This is as a result of pavement behavior modeling challenges [2]. PMS results are based on existing condition data collection. However, a reliable prediction method should be used to process the data. These models are used in programming and planning for following decisions [3]:

- Estimating type and time of Maintenance and Rehabilitation (M&R) policies to improve network condition;
- Predicting pavement remained life;
- Optimizing projects, M&R policies, and application time;
- Estimating life cycle cost; and,
- Evaluating long-term effects of various policies.

Pavement characteristics should be evaluated to model pavement deterioration. These characteristics include roughness, skid resistance, structural capacity and surface distress. Various indices are defined to evaluate these properties such as International Roughness Index (IRI) for roughness, Skid Number (SN) for skid resistance, Pavement Condition Index (PCI) and Pavement Quality Index (PQI) for general pavement condition evaluation [3].

Predicting pavement behavior is a complicated process since pavements are constructed from various materials. Numerical analyses like finite element models are employed to predict pavement behavior. Technology development in recent years increased computation speed which facilitates predicting deterioration occurrence time and rate [4].

Performance models are key components of any PMSs which may be applied during maintenance and rehabilitation analysis and subsequently budget optimization to identify the cost–effectiveness of different rehabilitation alternatives [5]. Pavement roughness is the major factor influencing pavement riding quality. It can be directly related to pavement performance and road network costs, through such factors as dynamic pavement loading, vehicle operating costs and vehicle fatigue [6]. AASHO Road Test indicated that about 95 percent of the information about pavement serviceability is contributed by surface roughness [3].

The main objective of this study is to develop a pavement performance model based on roughness, i.e. IRI applying the famous soft computing technique, Artificial Neural Network (ANN) algorithm using the Long-Term Pavement Performance (LTPP) data. The reason behind selecting LTPP data is its comprehensiveness (time and variable). Finally, the results of the developed ANN model, is compared with results of a polynomial nonlinear regression model.

2. Literature Review

2.1. Pavement Deterioration Prediction

Pavement deterioration models are being employed to predict future performance of a pavement section, identify the rehabilitation needs, and estimate the network conditions after the implementation of different M&R activates. Furthermore, these models may be utilized during M&R analysis and subsequently, budget optimization to identify the cost effectiveness of different M&R alternatives [7]. Accurate pavement deterioration modeling can help agencies to predict the network performance, estimate short-term and long-term budget requirements for preserving the network at or better than a predefined performance level threshold, or to analyze the effect of different funding levels on the network condition [8].

Pavement performance or deterioration prediction models can be either deterministic or probabilistic, depending on the method employed to simulate the deterioration or aging process. Deterministic models predict the condition on the basis of mathematical functions of observed or measured deterioration without taking into account the uncertainties associated with the deterioration process. On the other hand, probabilistic models take into account the uncertainties and predict the condition as the probability of occurrence in a range of possible outcomes [9].

Deterministic models are broadly applied by transportation agencies as they provide a simple approach to model the pavement deterioration in consonance with historic performance data. These models can be easily adjusted by calibration of the model parameters through feedback mechanisms, to better represent the local experience and future pavement performance data. They are typically developed as linear, convex, concave, or S-shaped curves to better describe the pavement performance [5].

Various models are introduced for pavement deterioration prediction which the most important of them are [3, 7, 10-11]:

- Empirical (Regression);
- Survivor curve;
- Markov chain;
- Semi-Markov;
- Bayesian;
- Trend Curve; and,
- ANN.

Empirical models are generally produced based on statistic methods and have been applied broadly to predict pavement deterioration for several years. Using such models needs a lot of pavement life data. For instance, Smith and Tighe [12] developed an empirical model for national and provincial pavements of Canada in 2004. This study revealed overlay thickness and environmental conditions have significant effect on pavement roughness unlike pavement subgrade type.

Soft computing based approaches have been effectively applied in order to model and predict mechanical behavior and material strength in the field of civil engineering [13-17]. In addition, artificial neural networks (ANNs) have been developed in recent years for pavement deterioration modeling. ANN has more modeling capability and less error than empirical models. Ozbey and Laub [2] developed an ANN model based on LTPP data and compared it with a linear regression model. In addition, Kargah-Ostadi et al. [18] developed a network-level pavement roughness prediction model using the same data. Flexible pavement roughness variations during the time under various M&R policies were studied and high correlation were obtained between the model output and the field data. This showed the high efficiency of the ANN models.

In addition, Markov chain as an example of probabilistic models, was presented by Porras-Alvarado et al. [9] to characterize pavement performance in support of pavement management decision makings. IRI data from the National Department of Transportation (DOT) in the Costa Rica was used for the numerical case study to illustrate the application of the developed methodological framework. The findings from this study demonstrated that the proposed methodological framework is a viable approach to modeling pavement deterioration process.

2.2. Roughness-Based Models

American Society for Testing and Materials (ASTM) defines pavement roughness as *"the deviations of a pavement surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads and drainage"* [19]. In recent years, transportation agencies widely used the IRI instead of the other indicators of pavement surface condition such as Present Serviceability Index (PSI). The IRI is computed as the cumulative movement of the suspension of the Quarter-Car System (QCS) (Fig. 1) divided by the travel distance [7]. The commonly recommended units are meters per kilometer (m/km), millimeters per meter (mm/m) and, inches per miles (in./mi).

Mohamed Jaafar et al. [20] developed a pavement roughness deterioration model employing Multiple Linear Regression (MLR) and ANN approaches. Datasets from 34 asphalt pavement test sections in the LTPP Southern U.S. states were analyzed. The independent variables were initial IRI, pavement age, Equivalent Single Axle Load (ESAL), design structural number, as well as the construction number. The MLR equations exhibited relatively low coefficient of determination (R^2) values compared to the ANN models. This analysis indicated that the ANN models with high R^2 values outperform the MLR equations in predicting the pavement roughness. It was recommended to deliberate construction number intervention (CN) factor as a dummy variable to take into account the M&R treatments on the pavement section in the pavement roughness modeling to improve the accuracy of the IRI prediction.

Khattak et al. [21] developed IRI models for overlay treatment of composite and flexible pavements in the state of Louisiana. Various factors affecting the IRI of overlay treatment were identified. New climatic factors were developed, regression analysis was conducted and IRI prediction models were generated. Such models could be applied as a suitable pavement management tool for pavement maintenance and rehabilitation actions.

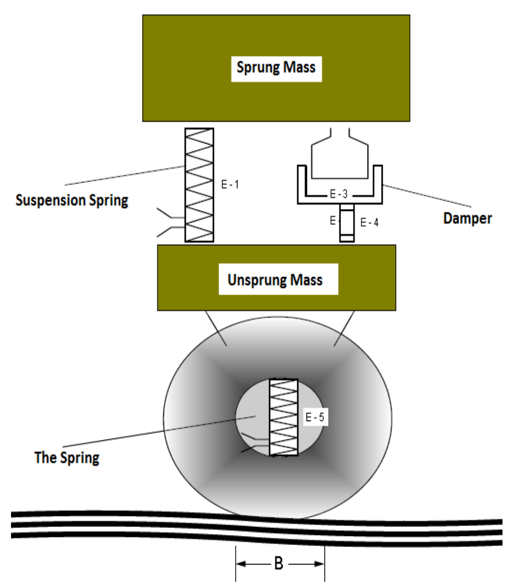

Fig 1. Quarter-car system [7].

Beckley [22] developed a methodology to evaluate and predict pavement roughness over the pavement service life. Unlike previous studies, a unique aspect of this work was the use of non-linear mathematical function, sigmoidal growth function, to model the IRI data and provide agencies with the information required for decision making in asset management and funding allocation. The analysis included data from two major databases: the LTPP and the Minnesota Department of Transportation MnROAD research program. This study aimed to demonstrate several concepts; that the LTPP and MnROAD roughness data could be represented applying the sigmoidal growth function, that periodic IRI measurements collected for road sections with similar characteristics could be processed to develop an IRI curve representing the pavement deterioration for this group, and that pavement deterioration using historical IRI data can provide insight on traffic loading, material, and climate effects.

Soncim and Fernandes [23] developed a roughness performance prediction model for double surface treatment highways. The factors considered were pavement age, traffic volume and climate, the last one mainly in terms of rainfall. An Analysis of Variance (ANOVA) was performed to assess the significance of the factors and to define the parameters of the performance model. The obtained model was compared to other roughness prediction models and reported better correlation between observed and predicted values, indicating the validity of its use in pavement management analysis of double surface treatment road networks.

Besides these attempts, Smith [24] considered some of the key factors that can influence the IRI of pavements. It was found that a greater number of asphalt lifts placed related to an improved IRI value for the project for up to 3-lifts. The pre-overlay rideability proved to be a major factor in the rideability of 1-lift overlay projects (rougher pavements initially are more likely to be rougher after overlay) exhibiting a logarithmic type relationship with the percent improvement. The thickness of the 1-lift overlays did not appear to be a critical factor after the pre-overlay IRI values were taken into account, however 2-lift overlays with an intermediate asphalt lift less than one inch thick did not show the same rideability improvement as a layer that was approximately 2 inches thick.

2.3. LTPP Program

The LTPP program was initiated in 1987 as a part of the Strategic Highway Research Program (SHRP). The main objective of LTPP is to establish a national long-term pavement database to support SHRP objectives and future needs [25]. The database includes information that has been systematically collected throughout the duration of the project for about 2,500 pavement sections for the past 30 years. Collected data includes construction information, pavement structure, material properties, maintenance and rehabilitation activities, pavement condition, pavement loading, as well as environmental condition information. LTPP database can be used to develop base deterioration prediction models for developing PMS in any states that can then be adjusted using agency-specific experience and/or data. In addition, LTPP data is a major source for calibrating Mechanistic-Empirical Pavement Design Guide (MEPDG) models [26].

The LTPP test sections are classified into a number of studies; General Pavement Studies (GPS) and Specific Pavement Studies (SPS) sections. A GPS test site typically would have one test section, while an SPS test site would have multiple test sections incorporating a controlled set of experiment design and construction features [25]. The data is collected in a consistent manner at a specific level of accuracy and checked through a series of Quality Assurance (QA) criterions. In addition, M&R activities are monitored and recorded, thus addressing some of the possible sources of inconsistencies in historic performance data. Through a pavement management approach, LTPP data can be tailored to fit the structure of a network-level PMS database and used to develop base performance models, which can then be adjusted applying local data from individual agencies to model the pavement performance in these agencies [5].

As an application, Nassiri et al. [27] focused on identifying significant variables to roughness development for Alberta's highway network. In this study, the data available in the PMS is used to develop two new prediction models for the IRI; one for new, and the other for straight overlaid asphalt concrete sections with a granular base. The model for new sections is validated using data from the GPS-1 in the LTPP database located in the provinces of Alberta, Manitoba and Saskatchewan in Western Canada.

3. Data Extraction

In this study, in-service flexible pavement sections from the LTPP database are adopted for analysis. When determining the dataset for this analysis, all available information on GPS-1 and GPS-2 sections (GPS-1: asphalt pavement with granular base, GPS-2: asphalt pavement with stabilized base) are scrutinized in the LTPP Standard Data Release (SDR v.23) database [28]. As a result, sections with at least one IRI evaluation after its first inspection were considered in this analysis. The sections selected cover the four representative regions of the United States according to LTPP [25]. Table 1 and Table 2 present final number of sections in each LTPP states for GPS-1 and GPS-2 pavements, respectively [23].

Table 1. Available GPS-1 sections with IRI data in each LTPP states.

State Code	Sites	State Code	Sites	State Code	Sites
1	7	23	10	47	2
2	13	25	10	48	99
4	43	26	9	49	5
6	14	27	25	50	6
8	10	29	8	51	7
9	4	30	9	53	15
11	1	31	9	56	6
12	30	32	5	81	11
13	8	33	3	82	3
15	4	34	12	83	13
16	16	35	5	84	2
17	2	36	2	85	4
18	5	37	27	87	8
19	3	42	10	88	1
20	8	45	6	89	7
21	5	46	7	90	13

Table 2. Available GPS-2 sections with IRI data in each LTPP states.

State Code	Sites	State Code	Sites	State Code	Sites
1	8	30	6	51	14
4	7	32	7	54	3
5	7	34	5	56	23
6	35	35	3	72	4
8	6	36	7	81	4
10	3	37	12	82	2
12	6	38	2	83	9
13	14	40	20	84	2
18	4	41	2	87	2
22	2	46	3	88	9
24	8	47	29	89	3
28	28	48	35	-	-
29	4	50	6	-	-

Used data include State_Code, SHRP_ID, Profile_Date, Construction_Number, Average_IRI and Run_Number for 18 years collected data from LTPP sections. The date of first inspection was contemplated as the initial time (zero time). Pavement ages were then calculated with respect to this initial date. Pavement ages and the ratio of desired IRI over initial IRI (IRI^0) that is presented as $\eta = IRI/IRI^0$ were calculated and used as the final input data for analysis.

4. Methodology

The main model of this study is produced applying Artificial Neural Network. ANN is an intelligent approach constructed from several neurons which perform coordinately solving a problem. These neurons are inspired from human being neural systems and process data like human's brain. In the other words, ANN tries to make machines which work like human's brain and could be trained by examples, similar to human.

There are four types of ANN including Back-Propagation Neural Network (BPNN), Radial Basis Function Networks (RBFN), Probabilistic Neural Networks (PNN) and Clustered Probabilistic Neural Networks (CPNN) [29]. In this study, BPNN was utilized for modeling pavement roughness since these methods showed better results in similar modeling efforts [29]. The learning mechanism of this network is a generalized delta rule (a rule to update neurons weights in a layer) that performs a gradient descent on the error space to minimize the total error between the actual calculated values and the desired ones of an output layer during modification of connection strength. Put it differently, a least mean square procedure is carried out which finds the values of the connection weights that minimize the error function by applying a gradient descent method. The training is accomplished in an iterative process. The procedure of training is summarized as following [30]:

Step 1- Assign initial values to connection strengths W_{ji} and W_{kj}, and to biases θ_j and θ_k.

Step 2- Input values net_{pi} become activation on the input neurons in an input layer.

Step 3- Training and testing patterns are prepared. In this study the time which in IRI is measured applied as input parameter in training and test patterns. The IRI to initial measured IRI ratio is the output variable.

Step 4- Calculate input values of a hidden layer j, net_{pj}, using the output values of an input layer i, O_{pi}, connection strength W_{ji}, and biases θ_j between an input layer i and a hidden layer j. Then, the output values of a hidden layer j, O_{pj}, are derived from net_{pj} and activation function $f(0)$:

$$net_{pj} = \sum_i W_{ji} O_{pi} + \theta_j \quad (1)$$

$$O_{pj} = f_j(net_{pj}) \quad (2)$$

where, $f(0)$ is an activation function. In this study, $f(0)$ is a sigmoid function; because sigmoid function can effectively deal with a balance between linear and nonlinear behavior, which is used commonly in the construction of BPNN:

$$f_x = {}^{1}/_{(1 + e^{\alpha x})} \quad (3)$$

where, α is the slope parameter of the sigmoid function.

Step 5- Calculate input values of an output layer k, net_{pk}, using the output values of a hidden layer j, O_{pi}, connection strength W_{kj}, and biases θ_k between a hidden layer j and an output layer k. Then, the output values of an output layer k, O_{pk}, are derived from net_{pk}:

$$net_{pk} = \sum_{j} W_{kj} O_{pj} + \theta_k \tag{4}$$

$$O_{pk} = f_k(net_{pk}) \tag{5}$$

Step 6- The error E between the calculated value O_{pk} and the desired value T_k of an output layer may be defined as:

$$E = \frac{1}{2} \sum_{k=1} (O_{pk} - T_k)^2 \tag{6}$$

In the BPNN, the error at output neurons is propagated backward to hidden layer neurons, and then to input neurons modifying the connections weights and the biases between them by a generalized delta rule. The modification of the weights and the biases in a generalized delta rule is implied through a gradient descent of the error. From hidden to output neurons:

$$\Delta W_{kj} = \eta\, \delta_k O_{pj} \tag{7}$$

$$\Delta B_k = \eta\, \delta_k \tag{8}$$

$$\delta_k = (T_k - O_{pk}) f'(net_{pj}) \tag{9}$$

where, η is the learning rate. And from input to hidden neurons:

$$\Delta W_{ji} = \eta\, \delta_j net_{pj} \tag{10}$$

$$\Delta B_j = \eta\, \delta_j \tag{11}$$

$$\delta_j = W_{kj} \delta_k f'(net_{pj}) \tag{12}$$

Step 7- Repeat step 1 to 6 until error E goes below a target error or iteration number exceeds the user-defined maximum iteration number.

Fig. 2 presents a simple architectural layout of BPNN that consists of an input layer, a hidden layer, an output layer and connections between them.

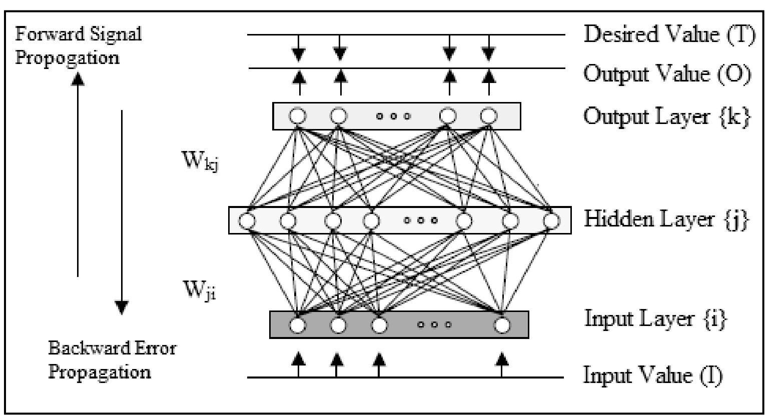

Fig. 2. Structure of BPNN [30].

5. Results and Discussion

A part of data in ANN can be used for training the network and the remained part for testing it. In this study, all of the data was applied to train and test BPNN. The reason is that the purpose of this study is not specifically to develop a model, but is to compare how ANN works versus other statistical methods. Sigmoid function with one hidden layer and 10 neurons was used for training process. Epoch counts were 1000 times and finally Mean Squared Error (MSE) in training process calculated as 0.00498 and 0.00767 for GPS-1 and GPS-2, respectively which was gained at last epoch. Learning rate was set to 1 in training process. "Neuro Solution" was used in this study as soft computing software. This is a Windows-based user-friendly software able to perform several analysis types such as cluster analysis, sales forecasting, sports predictions, etc. The advantage of this package versus other existing packages is that this is able to conduct all three steps of building, training and testing together. Final estimation results of BPNN are portrayed in Fig. 3 for GPS-1 and in Fig. 4 for GPS-2 pavement sections.

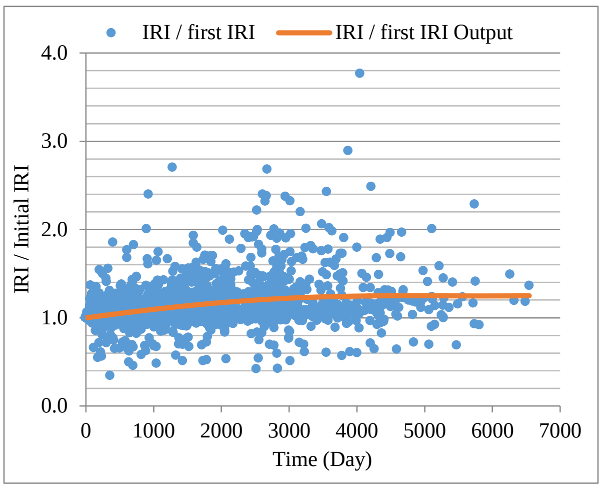

Fig. 3. LTPP Data (Points) and BPNN output (Line) for GPS-1 sections.

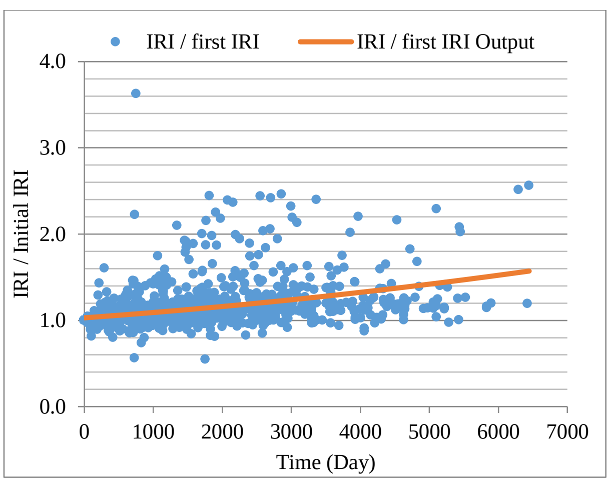

Fig. 4. LTPP Data (Points) and BPNN output (Line) for GPS-2 sections.

As it can be observed in these figures, at GPS-1 approach, IRI to initial IRI ratio reaches to a constant value after about eight years of pavement age; while in GPS-2, there is an almost constant increase rate in over about 18 years. This may be as a result of the stabilization of the base layers of GPS-2 pavements, that has affected on the roughness of these pavements in future years.

Several models were tested and the results obtained from Polynomial regression model with the power of three were more similar to BPNN results. Consequently, to evaluate BPNN output in this study, constructed model was compared with a polynomial regression model (with power of 3) which extracted by nonlinear regression method in SPSS software. To compare the models, some useful error equations were used and results are presented in Table 1. MSE was calculated according to Equation 13:

$$MSE = \frac{\sum_{j=1}^{N}\left(y_j - \hat{y}_j\right)^2}{N} \tag{13}$$

where, y_j is measured value of IRI/Initial IRI; $\hat{y}_j$ is the predicted value; and, N is the total number of analysis data.

As it can be seen in this table, the MSE values for ANN modeling approach are less than polynomial ones. Normalized Mean Squared Error (NMSE) was calculated for both approaches using Equation 14:

$$NMSE = \frac{MSE}{Var(y_j)} \tag{14}$$

where, $Var(y_j)$ is the variance of measured values of IRI/Initial IRI.

NMSE results are also less for ANN rather than polynomial modeling. The other error function, Mean Absolute Error (MAE) was utilized and results are reported in Table 3 which were computed confirming to Equation 15:

$$MAE = \frac{\sum_{j=1}^{N}|y_j - \hat{y}_j|}{N} \tag{15}$$

Table 3. Comparison of model performance indicators results.

Model Performance Indicator	Sections	Model Approach	
		ANN (BPNN)	Polynomial (Power 3)
MSE	GPS1	0.0430	0.0757
	GPS2	0.0449	0.0457
NMSE	GPS1	0.8616	1.5148
	GPS2	0.8237	0.8385
MAE	GPS1	0.1169	0.1524
	GPS2	0.1146	0.1245
Min AE	GPS1	3.18E-6	6.27E-6
	GPS2	1.18E-5	3.02E-5
Max AE	GPS1	0.5909	0.6564
	GPS2	0.5953	2.5129
MAPE	GPS1	10.48%	12.21%
	GPS2	9.16%	10.33%
RMSE	GPS1	0.2750	0.2751
	GPS2	0.2120	0.2139

The similar results were obtained for MAE analysis; however, in general ANN showed better results. Two other statistics analysis including Minimum Absolute Error (Min AE) and Maximum Absolute Error (Max AE) were performed using Equation 16 and Equation 17, respectively. Comparison results for both ANN and polynomial modeling approaches are reported in Table 3.

$$Min\ AE = min\{|y_j - \hat{y}_j|, i = 1, \dots, N\} \tag{16}$$

$$Max\ AE = max\{|y_j - \hat{y}_j|, i = 1, \dots, N\} \tag{17}$$

According to this table, for both GPS-1 and GPS-2 pavement sections, ANN model reveals more accurate prediction in comparison with the polynomial model. Mean Absolute Percentage Error (MAPE) was also calculated using Equation 18:

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{y_j - \hat{y}_j}{y_j}\right| \tag{18}$$

As expected, for MAPE the similar results were obtained. Finally, Root Mean Squared Error (RMSE) was computed in consonance with Equation 19:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_j - \hat{y}_j\right)^2} \tag{19}$$

Looking into the calculated errors for ANN (BPNN) and Polynomial models demonstrates less error for BPNN model as it was expected. Less error will lead to more precise decision makings in choosing M&R policy which will finally reduce consumed costs of pavement management.

6. Conclusions

In this study LTPP data extracted from GPS-1 and GPS-2 pavement sections were used for developing a pavement deterioration model. Modeling was according to IRI as an index for pavement roughness and used BPNN as an artificial neural network technique. After training and testing the final developed model, results were compared with a polynomial model made by nonlinear regression. The most beneficial statistics error analyses including MSE, NMSE, MAE, Min AE, Max AE, MAPE, as well as RMSE were employed to comparison. Results showed the developed ANN (BPNN) model could predict the roughness deterioration of the both GPS-1 and GPS-2 pavements with very good accuracy and less error in comparison with the polynomial regression model. In addition, the ability of ANN to model pavement performance modeling for application in any pavement management system was reported.

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