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Models Development for Asphalt Pavement Performance Index in Different Climate Regions Using Soft Computing Techniques

Abdualmtalab Abdualaziz Ali[1,2*], Usama Heneash[3], Amgad Hussein[4], Shaban Ismael Ali[5], Shahbaz Khan[6]

1. Ph.D. Candidate, Department of Civil Engineering, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, Newfoundland, Canada
2. Lecturer, Department of Civil Engineering, Faculty of Engineering, Azzaytuna University, Tarhuna, Libya
3. Assistant Professor, Department of Civil Engineering, Faculty of Engineering, Kafr El Sheikh University, Kafr El Sheikh, Egypt
4. Associate Professor, Department of Civil Engineering, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, Newfoundland, Canada
5. Associate Professor, Department of Civil Engineering, Faculty of Engineering, Near East University, North Cyprus
6. Postdoctoral Associate, Department of Civil Engineering, Faculty of Engineering, University of Florida, United States

Corresponding author: *aayali@mun.ca*

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ABSTRACT

The Pavement Condition Index (PCI) is one of the most critical pavement performance indicators and ride quality. This study aims to develop PCI models based on pavement distress parameters using conventional technique and artificial neural network (ANN) technique across two climate regions in the U.S. and Canada. The long-term pavement performance (LTPP) database was used to obtain pavement distress data, including pavement age, rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, and ravelling, as input variables for predicting PCI. Forty-three flexible pavement segments were considered with 333 observations. The type, severity, and extent of surface damage and the PCI were determined for each pavement segment. Two modelling techniques were conducted to predict the PCI, namely, multiple linear regression (MLR) and artificial neural network (ANN). The coefficient of determination (R2), Root mean squared error (RMSE), and mean absolute error (MAE) were used to examine the performance of the two techniques adopted in this study. The models' results determined that both ANN and MLR models could predict PCI with high accuracy; ANN models were more accurate and efficient. ANN provided the highest accuracy in predicting PCI of pavement for wet and wet no-freeze climate regions, with R2 values of 99.8%, 98.3 %: RMSE values of 0.44%, 1.413%, and MAE values of 0.44%, 1.022%, respectively. Whereas in the MLR method, R2 values of 86.8% and 89.4%: RMSE values of 7.195%, 7.324%, and MAE values of 5.616%, 5.79% for wet and wet no freeze climate regions, respectively.

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1. Introduction

The Pavement Management System (PMS) method is an efficient, effective method to ensure that all paved roads are maintained in satisfactory structural conditions [1,2]. Maintenance and rehabilitation strategies are crucial for improved ride comfort and traffic safety [3]. In addition, the cost of operation of vehicles, construction, and environmental impacts are reduced. Different indicators can be used to determine pavement quality, such as the Pavement Condition Index (PCI), International Roughness Index (IRI), and Present Serviceability Rating (PSR) [4,5]. A good PMS should have performance models, a centralized database, reports, and analysis tools [6]. Moreover, two other components need to be managed: a prediction tool for predicting pavement performance in the future and an optimization process that uses defined decisions to determine the most optimal conditions for pavements [7]. The distress identification manual developed during Long Term Pavement Performance (LTPP) serves as a reference manual for classifying distress [8]. The ability to predict pavement deterioration at the network level ensures that resources are allocated appropriately, and that plans are prioritized, while at the project level, a reasonable prediction enables the project managers to know what maintenance measures are needed ahead of time [9,10]. Most states use in the US some pavement condition assessments. This includes pavement condition rating (PCR), PCI, pavement quality index (PQI), condition score, pavement serviceability rating (PSR), surface condition index, and pavement distress index (PDI). However, PCI is one of the popular methods used by Arkansas, California, Hawaii, Idaho, Indiana, Vermont, Ohio, Lousiana, Minnesota, Texas, and Lowa. PCI helps in deciding the maintenance strategy at the network level [11].

The PCI method is commonly used to evaluate changes in road network systems and was developed by the U.S. Army Corps of Engineers [12,13]. As recently as a few years ago, transportation agencies worldwide have been using PCI data to decide on constructing, repairing, and maintaining airfields, roads, and parking lots. Their studies used visual survey results (through imagery or field inspections) to determine pavement distresses' type, severity, and quantity. The PCI method effectively assesses a structure's integrity, is a reliable indicator of current and future performance, and does not require structural testing or skid resistance or roughness [12,14]. According to Shahin and Kohn [15], PCI is a pavement condition number rating of 0 to 100, the worst-case rating is 0, and the best-case condition is 100, as shown in Figure 1. The method of calculating PCI for the flexible pavement system [16,17] is to assess the intensity and the extent of each distress initially. This study aims to develop PCI models based on pavement distress parameters using conventional technique and artificial neural network (ANN) technique and to compare the performance of the models using various statistical measures such as coefficient of determination (R), root mean square error (RMSE) and mean absolute error (MAE).

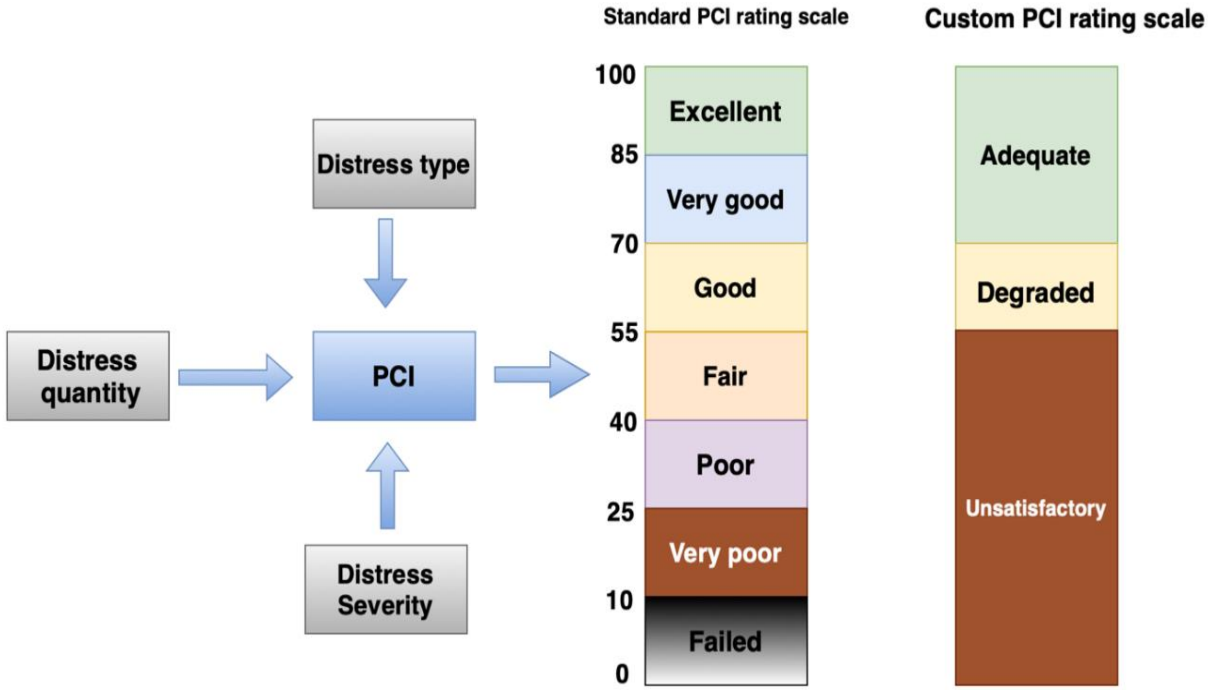

Fig. 1. Rating scale used for Pavement Condition Index (PCI) Method [17].

2. Literature review

Most previous PCI models are primarily based on linear or nonlinear regressions. In recent years, Researchers have conducted much research using fuzzy logic and artificial neural networks. They have proposed various forecasting methods, theories, and models considering the complex and numerous factors affecting pavement performance, such as traffic, environmental, and pavement operation parameters.

Fathi et al. [18] predicted fatigue distress using a vehicle training technique that combined RF and ANN techniques. The Support Vector Machine (SVM) method was used by Fujita et al. [19] to investigate cracks in asphalt pavement. Karballaeezadeh et al. [20] Gaussian process regression (GPR), Tree and Random Forest were applied to assess the structural capabilities of coatings on flexible pavements. Based on response surface methodology (RSM), Ghanizadeh and Naseralavi developed an equation for calculating the structure number (SN)in the 1993 AASHTO flexible pavement structural design guide [21].

Other researchers applied ANN and SVM methods to model acoustic longevity where maximum aggregate size, binder content, air void content, vehicle speed, and thickness were input variables [22]. Zeiada et al. [23] employed Gaussian Process Regression (GPR), Support Vector Machine (SVM), Ensemble, and Artificial Neural Network to model pavement performance in warm climates (ANN). Ali et al. [24] applied a fuzzy inference system (FIS) to predict pavement condition Index (PCI) based on pavement distress.

Meharie and Shaik used ANN, SVM, and RF techniques to compare the performance of models in predicting the cost of construction projects during the project's early conceptual phase [25]. Bhardwaj and Chaurasia used ANN, decision tree (DT), and RF models to compare the performance of liquefaction potential [26]. Sefene et al. [27] concluded that the RF technique improves the predictability of ambient temperature compared to Decision Trees (DT, and Gradient Boosting (GB).

The artificial neural network (ANN) is a tool for analyzing and solving complex non-traditional problems using highly interconnected neurons [28]. ANNs are highly versatile and scalable tools that can be used to model and analyze complex statements. ANNs can be used in traditional methods, including finite element calculation of conventional statistical analysis [10,29]. The authors concluded that the ANN technique improved the predictability of dynamic modulus (E*) values [30]. Eidgahee et al. [31] applied the ANN, Genetic Programming (GP), and the Combinatorial Group Method of Data Handling (GMDH-Combi) techniques to the predictability of dynamic modulus of hot mix asphalt.

An ANN network consists of three elements as shown in Figure 2: (1) an input layer or processing element, (2) one or more hidden layers, and (3) an output layer of neurons. Data are typically received in the input layer from the outside environment, and the input layer neurons transmit this information to the hidden layer neurons without calculating anything. The hidden layer consists of one or more layers with many processing units. All neurons except those in the input layer compute a linear combination of the data from the previous layer and add a bias to it. The neural network must have a certain number of hidden neurons to be an accurate model. Highly nonlinear components require more neurons, whereas smoother items require fewer neurons [32]. Neuronal networks must have at least one hidden layer [33].

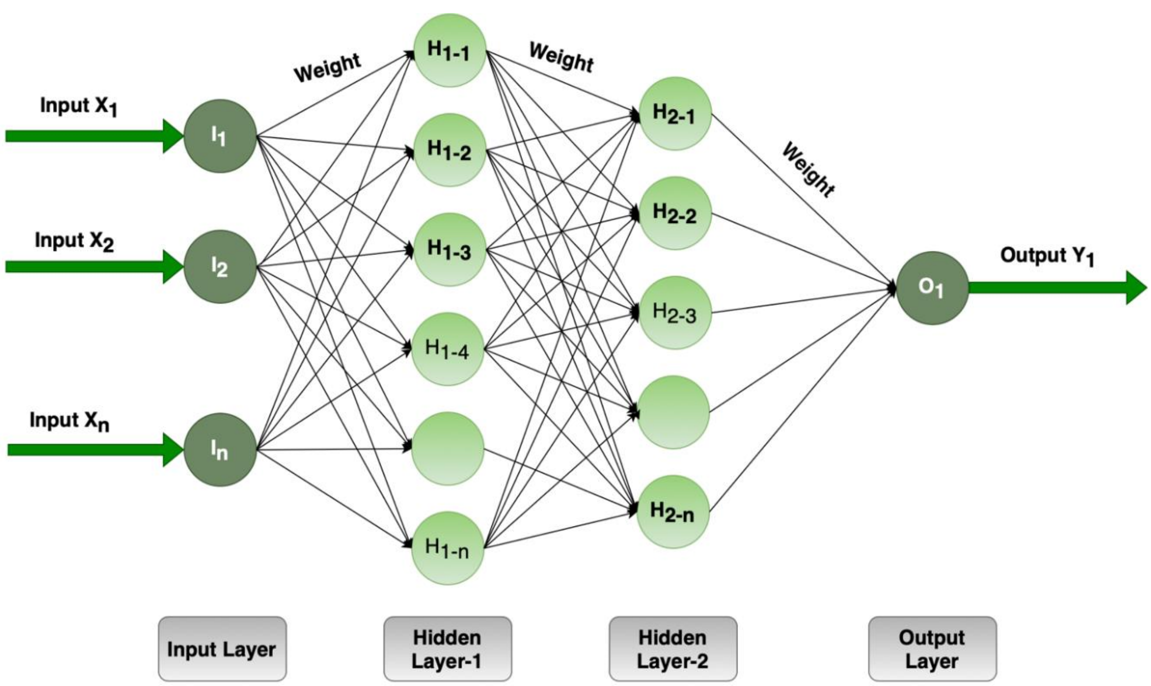

Fig. 2. The general architecture of the feedforward backpropagation ANN.

According to Sen and Gibbs [34], it is unclear how many hidden layers would be sufficient or how many nodes should be used in the hidden layers. Many interconnections between their neurons or processing elements give ANNs, which mimic the biological nervous system, their distinctive impact. They provide significant advantages by learning from examples and generating meaningful and cost-effective solutions for problems. Minor errors, such as a slight variation between the predicted and observed values, are ignored [35]. ANNs adapt to changing circumstances and digest information quickly [36]. ANNs can be composed of a single layer or many layers, depending on the complexity of the data. Multilayered neural networks have more than one hidden layer consisting of neurons without a direct connection to the network inputs or outputs.

Alternatively, using regression analysis, Ahmed et al. [37]developed PCI models for pavement distress on flexible pavements. The model yielded an R^2 of 78.4%, described by equation 1. Similarly, Shakir [38] developed a PCI model for pavement distress and traffic volume on flexible pavements. The model yielded an R^2 of 79%, as described by equation 2. Additionally, Ali et al. [39] developed a PCI predictive model for St. John's roads. The model was for 19 urban roads and yielded a coefficient of determination of R^2 of 48% as given in equation 3.

$$PCI = 85.3360 - 0.4415\times \text{Slippage} - 2.3254 \times\text{Potholes} - 37.2875 \times\text{rutting} \tag{1}$$

$$PCI = 98.861 - 0.407\times\text{Age} - 0.235\times\text{Cracking area} - 0.065\times\text{Longitudinal} + 3.404\times\text{Maintenance effect} - 0.003 \times\text{ESAL} \tag{2}$$

$$PCI = 47.22+0.91\times\text{Rutting} +3.11\times\text{Block} - 2.70\times\text{Fatigue} +1.69\times\text{Longtiudinal} +0.71\times\text{Transverse cracking} -1.81\times\text{Delamination} - 2.44\times\text{Potholes} - 0.14 \times\text{Patching} \tag{3}$$

3. Materials and methods

3.1. Methodology

This paper developed multiple regression analysis and algorithm optimization for various prediction models. An essential aspect of this study's methodology is developing prediction models and establishing accurate deterioration models based on machine learning techniques, such as artificial neural network (ANN). The ANN technique is used to guide models to pavement performance that can more accurately predict pavement conditions. Figure 3 illustrates the overall methodology of the study. This research examined two techniques: Multiple Linear Regression (MLR) and Artificial Neural Networks (ANNs), and compared them to predict PCI values. The present study was divided into three phases as follows:

- Development of asphalt pavement performance index (PCI) using the Multi-Linear Regression (MLR) technique.
- Development of asphalt pavement performance index (PCI) using Artificial Neural Network (ANN) technique.
- Compare and validation of the MLR and ANN models.

Multiple linear regression (MLR)

The research was conducted in two climate regions in the U.S. and Canada to evaluate the effects of different pavement distresses on PCI indicator values from LTPP. MLR is typically used to research the relationship between independent and dependent variables. The conventional regression method is comprehensive and robust in evaluating relationships between independent and dependent parameters. Equation 4 presents basic equations of the prediction models to find the influence of pavement distress on PCI value.

$$\text{PCI}=\text{C}+a_1X_0+a_2X_1+a_3X_2+a_4X_3+a_5X_4+a_6X_5+a_7X_6+a_8X_7+a_9X_8+a_{10}X_9 \quad (4)$$

where: PCI =Pavement Condition Index, C= Constant, X_0= Age, X_1= Rutting, X_2= Fatigue Cracking, X_3= Block Cracking, X_4=Longitudinal Cracking, X_5=Transverse Cracking, X_6=Patching, X_7=Potholes, X_8=Bleeding, X_9=Ravelling, an $a_1, a_2, a_3 \dots\dots\dots\dots a_{10}$= Coefficients.

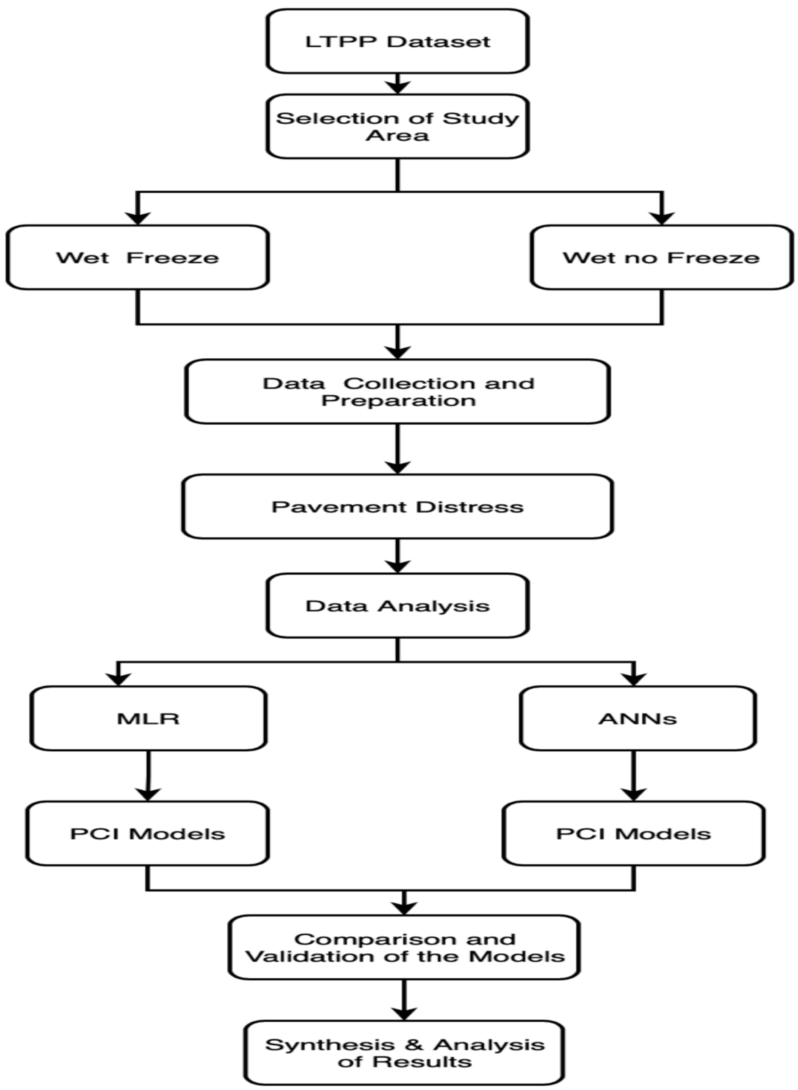

Fig. 3. Flowchart Research Methodology.

Artificial Neural Network (ANN)

The network that has been used in this research was a forward feed network. This network was trained with the backpropagation method. The architectural network for PCI consists of an input layer (10 parameters), three hidden layers, and an output layer. The output layer has one neuron (PCI). The ANNs technique is an important tool for developing prediction models by simulating human biological neurons' work and finding the best resolution for complex problems instead of using traditional approaches [40,41]. One of the most effective methods for developing prediction models is a feedback multilayer perceptron (FBMLP), used in this research. An FBMLP has three layers, as follows:

1-The first layer is the input layer x_i. In this study, the input variables are pavement distress.

$$x_i = (x_{1i}, x_{2i}, x_{3i}, \dots \dots x_{ai}) \quad (5)$$

i=1,2 3, ……., n.

2 - The second layer is the hidden layer, and it is used to connect the input layer with the output layer.

3-The third layer is the output layer y_i and the output variable is PCI.

$$\mathrm{y_i} = (\mathrm{y_{1i}}, \mathrm{y_{2i}}, \mathrm{y_{3i}}, \dots \dots \mathrm{y_{ai}}) \quad (6)$$

where i=1,2 3, ……., n.

A weighted sum of the values of the input parameters is computed through Equation (7):

$$\mathrm{Y}=\sum_{i=1}^{n} w_i\, x_i + w_0 \quad (7)$$

where w_i= weight associated with the I th input parameter; x_i = data corresponding to the input parameter; and w_0 = bias.

The hyperbolic tangent as expressed in Equation (8) is adopted in this study.

$$f(a) = \frac{2}{1+e^{-2n}} - 1 \quad (8)$$

A literature review of the existing PCI prediction models for various pavement types revealed that:

- ANN models have demonstrated exemplary performance in predicting and determining the Pavement Condition Index.
- Despite the benefits of the ANN technique, some authors consider ANN models to be a "black box" because it is impossible to know the precise effect of each variable on the prediction model [42,43].

3.2. LTPP database in pavement research

The long-term performance pavement (LTPP) is a program that was initiated in 1987 as part of the Strategic Highway Research Program (SHRP). The FHWA continued to work and extended the SHRP program after its completion in 1992 [44]. The pavements in the LTPP program are divided into two types: special pavement studies (SPS) at approximately 1,600 sites, and general pavement studies (GPS) at around 800 sites. These datasets were extracted, revised, then analyzed, and combined into a reliable and exhaustive data set. The authors examined 10 variables listed in Table 1. The authors selected 333 observations from 43 road sections in the U.S. and Canada that were used to develop PCI prediction models. Ten pavement distress variables are evaluated to predict PCI for wet and wet no-freeze conditions. These variables include age, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, ravelling, and rutting. The ASTM D6433-18 method was used to calculate PCI values. The method of calculating PCI for the flexible pavement system [16,17] is to assess the intensity and the extent of each distress initially. After that, the distress density is calculated using Equations 9, 10 and 11.

$$\text{Density} = \frac{\text{Distress area m}^2}{\text{Section area m}^2} \times 100 \tag{9}$$

$$\text{Density} = \frac{\text{Distress amount in the linear m}^2}{\text{Sample unit area in m}^2} \times 100 \tag{10}$$

$$\text{Density} = \frac{\text{Number of potholes}}{\text{Sample unit area in m}^2} \times 100 \tag{11}$$

Subsequently, deduct points (D.P.) from standard deduct value curves is determined for each distress type. Finally, PCI is determined from the total deduct value (TDV) using the corrected deduct value (CDV). A typical deduct value is given in Figure 4. More information about PCI calculation can be found in ASTM D6433-18.

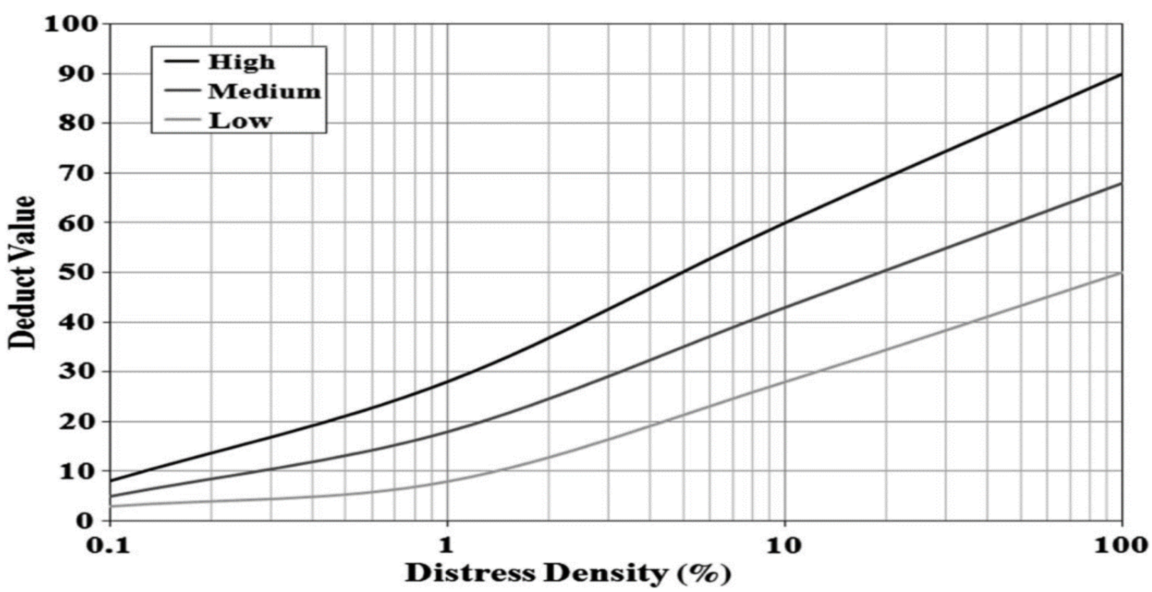

Fig. 4. Typical Deduct Value Curve [45].

Table 1
Details of Study Sections.

Parameters	Climate Regions									
	Wet Freeze					Wet no Freeze				
	Range		Mean		Std. Deviation	Range		Mean		Std. Deviation
	Minimum	Maximum	Statistic	Std. Error		Minimum	Maximum	Statistic	Std. Error	
Number of data samples	144					189				
Age (Year)	3	33	15.07	0.57	6.90	1	31	14.330	0.517	7.103
Rutting (mm)	0	29	8.44	0.46	5.53	0	22	7.050	0.305	4.194
Fatigue Cracking (m^2)	0	218.7	24.34	4.08	48.85	0	377.9	20.36	4.464	61.204
Block Cracking (m^2)	0	0	0	0	0	0	0	0	0	0
Longitudinal Cracking(m^2)	0	342.7	92.36	9.79	117.05	0	337.1	48.78	5.908	80.797
Transverse Cracking(m^2)	0	293	31.94	4.64	55.58	0	193	18.05	2.362	32.390
Patching (m^2)	0	0	0	0	0	0	0	0	0	0
Potholes(Number)	0	0	0	0	0	0	0	0	0	0
Bleeding (m^2)	0	350.8	18.19	5.49	65.94	0	0	0	0	0
Ravelling (m^2)	0	564.3	37.66	10.04	120.559	0	0	0	0	0
PCI %	8	91	77.77	1.65	19.877	8.0	100.0	71.45	1.645	22.618

4. Evaluation of regression and neural network models

The results of this study have been validated by applying three statistical criteria, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Equations 12, 13 and 14 below are used to calculate these criteria:

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2} \tag{12}$$

$$\text{MAE}=\frac{1}{n}\sum_i^n |t_i - o_i| \tag{13}$$

$$\text{RMSE}=\sqrt{\frac{\sum_i (t_i - o_i)^2}{n}} \tag{14}$$

$o\ \ i$ = actual value observation i; ti = predicted value of observation I, and n = number of observations.

5. Results and discussion

5.1. Multiple linear regression (MLR) results

The PCI Regression models are shown in equations (15) and (16), which consider pavement distress, cracking by rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, and ravelling as input variables and PCI output variables.

- **Wet Freeze Climate**

Equation 15 indicates the PCI model in the wet freeze region. The model showed that PCI is negatively correlated with age and fatigue cracking. The PCI model has been positively associated with rutting, longitudinal cracking, transverse cracking, bleeding, and ravelling. However, there are still some contradictions between the PCI and a few influencing variables.

$$\mathrm{PCI} = 116.52 - 2.74X_0 + 0.178X_1 - 0.018X_2 + 0.004X_4 + 0.024X_5 + 0.010X_8 + 0.008X_9 \quad (15)$$

- **Wet no Freeze Climate**

The PCI model in the wet no freeze region is indicated in equation 16. The model demonstrates that PCI has negatively correlated with age and longitudinal cracking. The PCI model has been positively associated with rutting and transverse cracking.

$$\mathrm{PCI} = 113.33 - 3.078X_0 + 0.205X_1 + 0.007X_2 - 0.004X_4 + 0.045X_5 \quad (16)$$

The correlation coefficient (R^2) of the wet freeze and wet no freeze relationship is 86.8% and 89.3%, respectively. Table 2 shows the summary of MLR models used in the wet freeze and no freeze region.

MLR Model Performance Validation

For validation purposes, cross-validation tests and sensitivity tests were conducted between the predicted and measured values for PCI.

- **Cross-Validation**

Cross-validation is either used to determine how accurately PCI models can forecast or to assess the consistency of the model across multiple data samples. 80% of the data samples for each category are randomly selected to construct deterioration models. The remaining 20 % of the data samples are used to test the empirical model's accuracy. Figures 5 and 6 show each climate area's deterioration model.

As seen in Table 3, the reduction in R^2, RMSE and MAE values for roads in the wet freeze and wet no freeze are insignificant. However, the accuracy reductions are 10.83 % and 3.56% for the same variables in the R^2value, respectively, while RMSE and MAE are 4.003%, 17.79%, 6.416%, and 6.01%, respectively. The MLR methods can accurately predict PCI models of pavement distress in two climate regions (wet freeze and wet no freeze).

Table 2
Summary of Performance of MLR Models.

Independent variable	Climate Regions and Coefficients							
	Wet Freeze				Wet no Freeze			
	Unstandardized Coefficients		Standardized Coefficients		Unstandardized Coefficients		Standardized Coefficients	
	B	Std. Error	Beta	t	B	Std. Error	Beta	t
R^2	86.8				89.3			
p-value	0.04				0.041			
Constant	116.456	1.723	-	67.576	113.33	1.54	-	73.608
Age	-2.733	0.105	-0.947	-26.116	-3.074	0.082	-0.967	-37.314
Rutting	0.178	0.119	0.049	1.492	0.205	0.135	0.037	1.47
Fatigue Cracking	-0.018	0.014	-0.044	-1.235	0.007	0.009	0.02	0.776
Longitudinal Cracking	0.004	0.003	0.013	0.406	-0.004	0.008	-0.015	-0.542
Transverse Cracking	0.024	0.013	0.068	1.929	0.045	0.02	0.065	2.186
Bleeding	0.01	0.01	0.033	1.022	-	-	-	-
Ravelling	0.008	0.005	0.051	1.604	-	-	-	-

Table 3
Cross-Validation Deterioration Models Result.

Climate Regions	**Statistical Error Measures (PCI)**								
	MLR			**Cross-validation**			**Reduction % (±)**		
	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**
Wet Freeze	86.8	7.195	5.616	77.4	7.495	6.001	-10.83	+4.003	+6.416
Wet no Freeze	89.3	7.324	5.79	92.6	8.909	6.16	+3.56	+17.79	+6.01

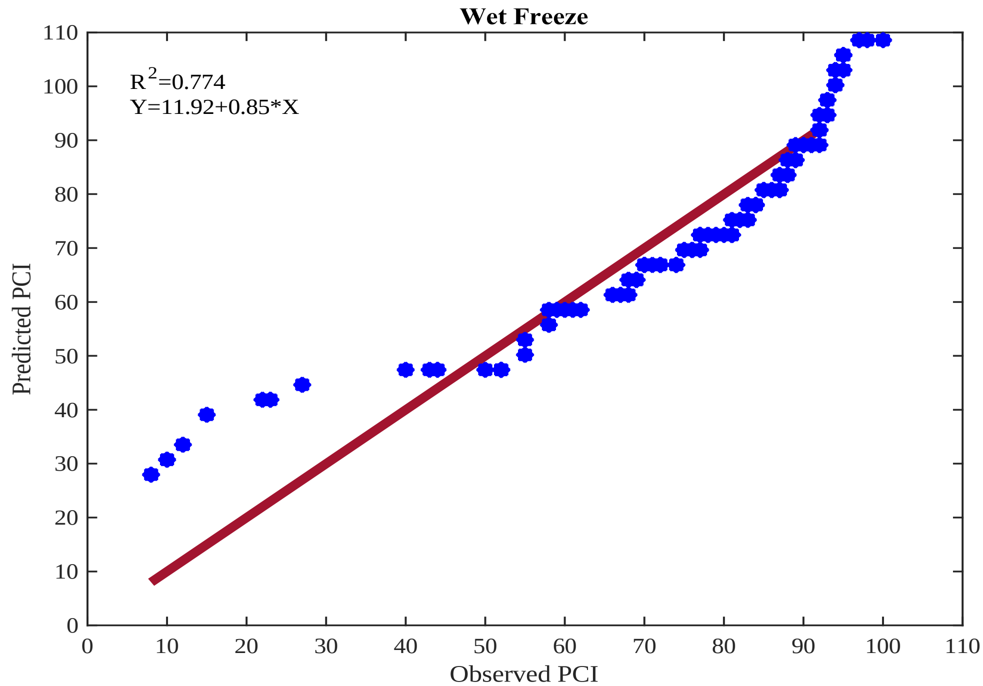

Fig. 5. Deterioration model for the wet freeze region.

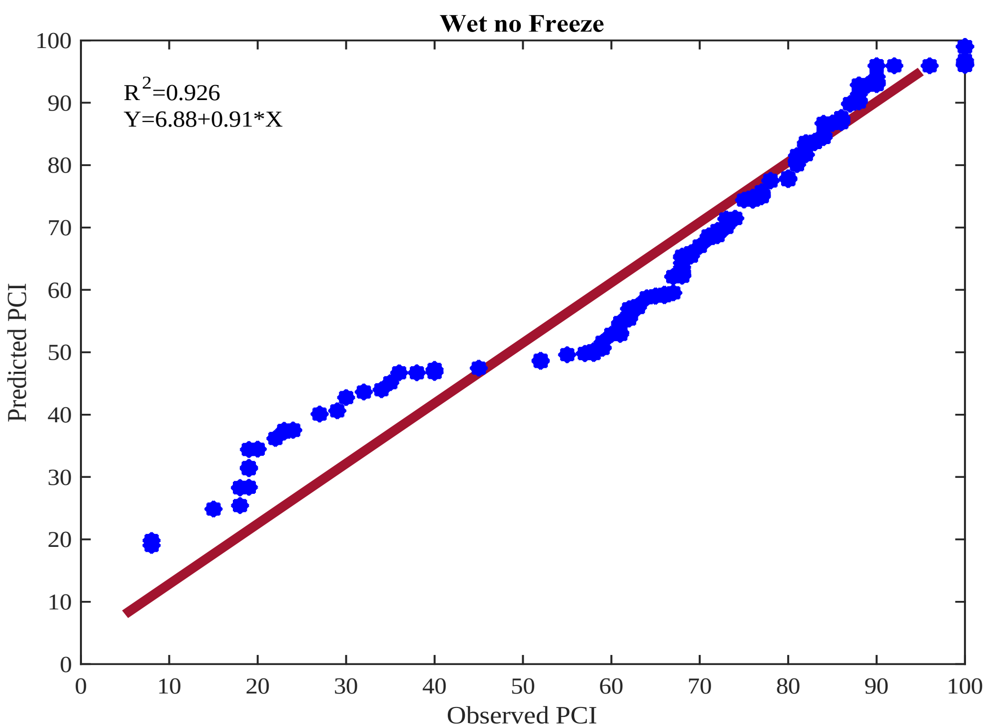

Fig. 6. Deterioration model for the wet no freeze region.

MLR Model Sensitivity Analysis

To develop an accurate PCI prediction model, an analysis of sensitivities is essential in any study that includes multiple inputs. The sensitivity index indicates which independent factor generates the most significant input into the generated dependent variable and which independent variable is the least effective. MLR using the backward elimination approach is conducted using the IBM SPSS package. The sensitivity analysis results are presented in Equations (17) and (18). The correlation coefficient (R^2) for equations 17 and 18 are 86.3% and 89.3% respectively, Tables 4 and 5 illustrate the Correlation matrix between variables utilizing the Pearson correlation coefficient.

$$PCI = 118.004 - 2.74X_0 + 0.178X_1 + 0.021X_5 + 0.009X_9 \quad (17)$$

$$PCI = 113.42 - 3.07X_0 + 0.175X_1 + 0.007X_2 + 0.045X_5 \quad (18)$$

As observed in Table 4, age showed a strong negative correlation of -0.93 with the PCI, which means with an increase in age the PCI decreases. Similarly, fatigue cracking, transverse cracking, longitudinal cracking, and rutting negatively correlate with the PCI. Fatigue cracking and transverse cracking are the second and third most significant factors for the decrease in PCI. While block cracking, patching, and potholes have no correlation with PCI. The influence of block cracking, patching and potholes can be due to the limited number of data available in the LTPP for these factors. Similarly, in Table 5, age showed a strong negative correlation with the PCI, and Transverse cracking has a low negative relationship with PCI. Rutting, fatigue cracking, and longitudinal cracking have a minor relationship with PCI. While block cracking, patching, potholes, bleeding, and ravelling have no correlation with PCI.

Tables 4
Correlation matrix between variables for wet freeze.

	PCI	Age	Rutting	Fatigue cracking	Block cracking	Long	Transverse	Patching	Potholes	Bleeding	Ravelling
PCI	1										
Age	-0.93	1									
Rutting	-0.15	0.2	1								
Fatigue cracking	-0.39	0.4	0.11	1							
Block cracking	0	0	0	0	1						
longitudinal	-0.19	0.24	-0.27	0.12	0	1					
Transverse	-0.28	0.35	-0.03	0.32	0	0.45	1				
Patching	0	.	0	0	0	0	0	1			
Potholes	0	0	0	0	0	0	0	0	1		
Bleeding	0.01	0.03	-0.07	-0.03	0	0.16	0.04	0	0	1	
Ravelling	0	0.06	0.05	0.08	0	-0.01	-0.05	0	0	0.15	1

Tables 5

Correlation matrix between variables for wet no freeze.

	PCI	Age	Rutting	Fatigue cracking	Block cracking	Long	Transverse	Patching	Potholes	Bleeding	Ravelling
PCI	1										
Age	-0.94	1									
Rutting	0.01	0.04	1								
Fatigue cracking	-0.09	0.13	-0.08	1							
Block cracking	0	0	0	0	1						
longitudinal	-0.09	0.12	0.24	0.05	0	1					
Transverse	-0.26	0.34	0.19	0.26	0	0.45	1				
Patching	0	0	0	0	0	0	0	1			
Potholes	0	0	0	0	0	0	0	0	1		
Bleeding	0	0	0	0	0	0.16	0	0	0	1	
Ravelling	0	0	0	0	0	0	0	0	0	0	1

5.2. Artificial neural network (ANN) models results

The performance models were assessed using three standard methods, the R^2 value, RMSE, and MAE. The R^2 value, which is a method to calculate the correlation between observed and predicted values, close to 1, reflects a strong relationship between the predicted values from the ANNs model and observed values. The lower the RMSE and MAE values, the lower the prediction error. As a result, they were obtained from the three models. The best neural network model was obtained by utilizing a variety of network structures and training algorithms, including a backpropagation learning approach with the Levenberg-Marquardt training algorithm (10-14-10-10-1-1). Random distribution was used to divide the data into the following three groups: training (70%), testing (15%), and validation (15%). MATLAB 2021a, with its neural network (NN) toolbox was used to analyze the data. Table 6 summarizes all the results for ANN, presenting the PCI model's R^2, RMSE and MAE values for two climate regions. Figures 7 and 8 show the ANN prediction results for PCI models for two climatic regions, i.e., wet freeze and wet no freeze.

Table 6 presents R^2, RMSE and MAE values of the PCI model for two climate regions for the (333 observations) flexible pavement sections in the two climatic regions. The highest R^2 value was 99.8% for wet freeze. The lowest R^2value for PCI 98.3% was observed for wet no freeze climate regions. The lowest RMSE and MAE values for PCI were 0.44% and 0.44% and were observed for the wet freeze climate region.

Table 6
Performance of ANN Models.

Climate Regions	Procedure	ANN Model		
		R^2	RMSE	MAE
Wet Freeze	Training	0.999	0.12	0.12
	Testing	0.996	0.84	0.84
	Validation	0.998	1.5	1.5
	All	0.998	0.44	0.44
Wet no Freeze	Training	0.984	1.994	1.434
	Testing	0.986	4.115	4.115
	Validation	0.984	0.964	0.729
	All	0.983	1.413	1.022

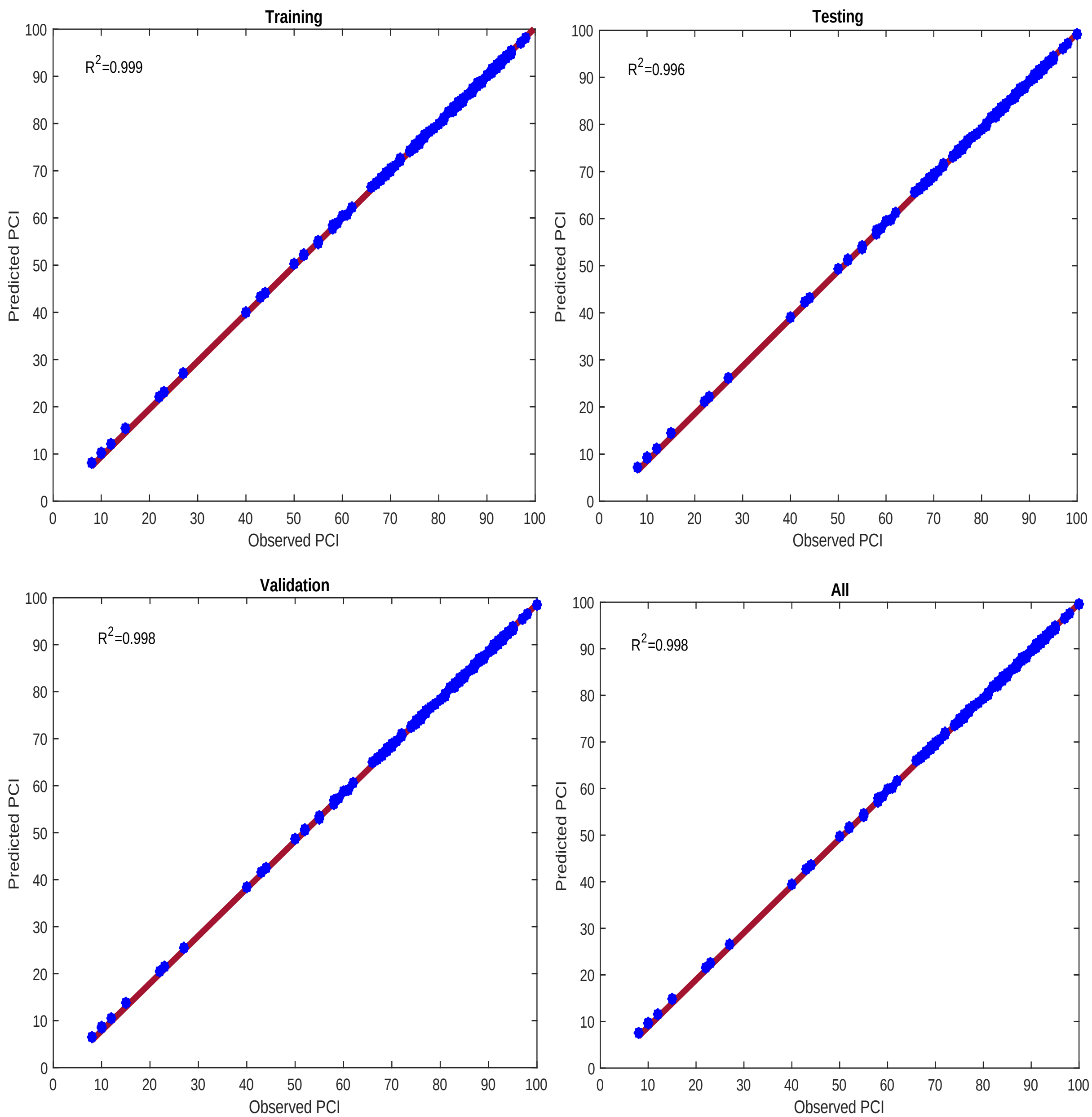

Fig. 7. ANN Model for Wet Freeze.

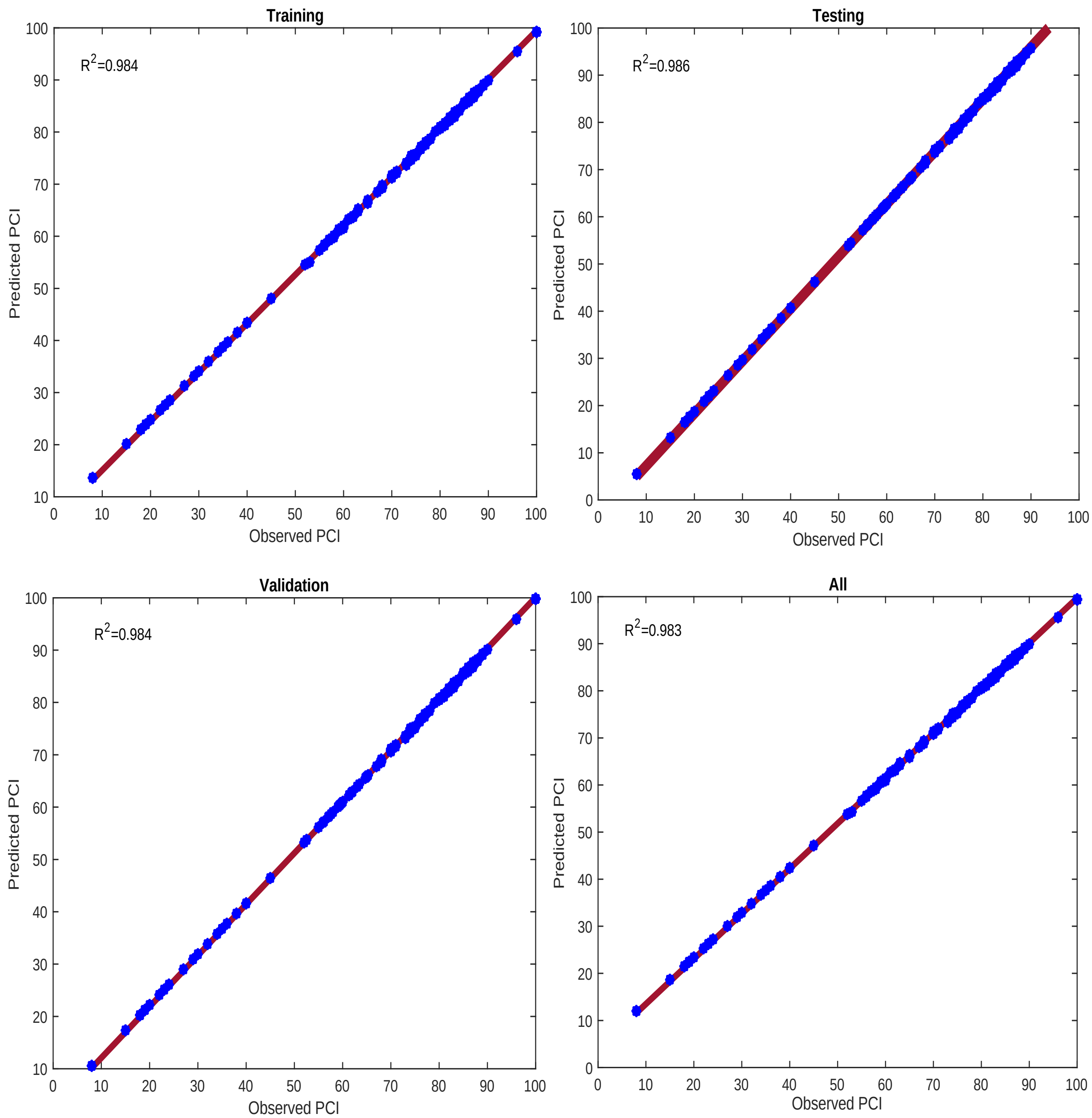

Fig. 8. ANN Model for Wet no Freeze.

6. Comparison of the MLR generated and ANNs model

ANNs model development has been carried out using the same data as regression model development. Comparing the ANN model to the MLR, the ANNs model had a better fit in the goodness of fit parameter according to Table 7. Figures 8 and 9 show the comparison of the MLR models to the ANN models for PCI.

Table 7
Comparison Between MLR and ANN Model.

Statistical Error Measures									
Climate Regions	MLR Generated			ANNs Generated			Improvement (%)		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
Wet Freeze	86.8	7.195	5.616	99.8	0.44	0.44	+13.03	+93.88	+92.17
Wet no Freeze	89.4	7.324	5.79	98.3	1.413	1.022	+9.05	+80.71	+82.35

Table 7 presented a comparison between MLR Generated and ANN models and summarized several points as follows:

- Prediction models based on the MLR and ANN techniques based on pavement distress volume have been developed in this study.
- ANN models provided more accurate predictions than MLR models.
- The statistics indicated R^2values from the ANN models are higher than the R^2values of the MLR models by 13.03 % and 9.05% for wet freeze and wet no freeze regions, respectively.
- The RMSE values of the ANN models are less than the RMSE values of the MLR models by 93.88% and 80.71%for wet freeze and wet no freeze regions, respectively.
- The MAE values of the ANN models are less than the MAE values of the MLR models by 92.17% and 82.35% for wet freeze and wet no freeze, respectively.

Several conclusions can be drawn from the data in Figures 9 and 10:

- The MLR approach has a slight corrugation while ANN has a straight line, which explains why ANN models tend to be more accurate.
- Figures clearly show that the ANN prediction models provided more accuracy than the MLR models under different climate conditions.

According to the results, the pavement distress model can predict the PCI models with high accuracy when used in different climate regions conditions.

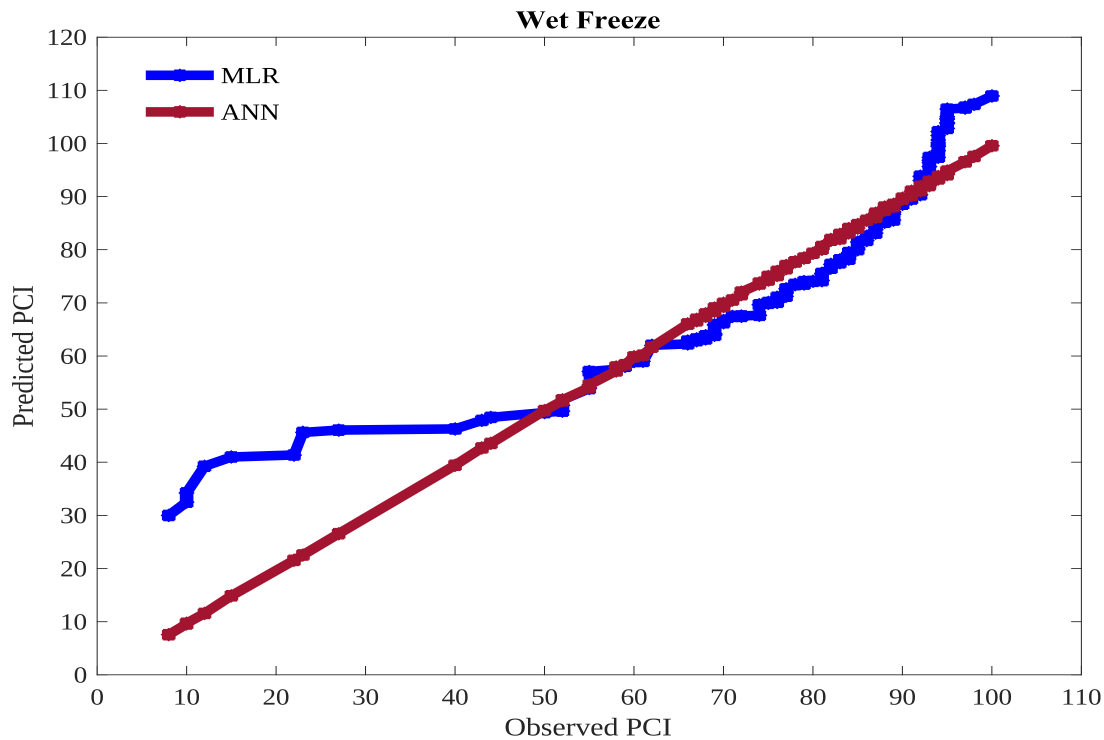

Fig. 9. Comparison between the Collected and Predicted PCI Using MLR and ANN Models for wet freeze.

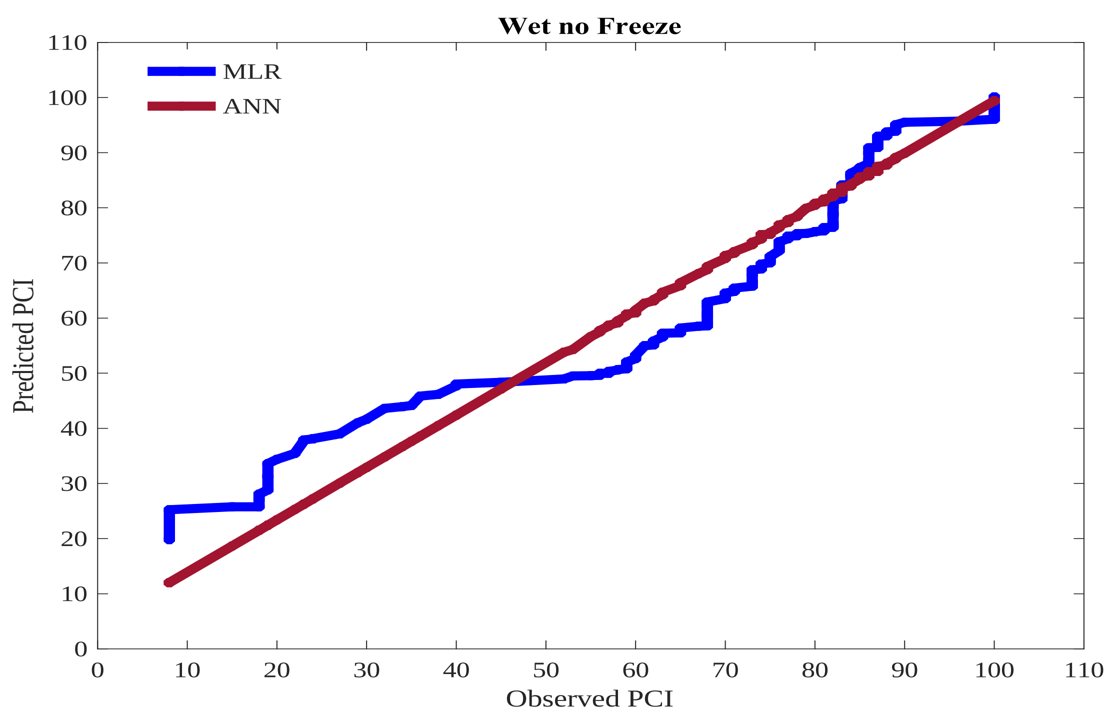

Fig. 10. Comparison between the Collected and Predicted PCI Using MLR and ANN Models for wet no freeze.

7. Conclusions

This present study proposed an approach to illustrate the relationship between the (PCI) indicator in asphalt pavements and ten independent variables (age of pavement and nine pavement distresses) more precisely and statistically reliable. The pavement distress data collected on wet freeze and wet no freeze climate regions in the U.S. and Canada are used in the present study to develop PCI models. This study investigates pavement distress parameters and predicts the PCI of flexible pavements, using 43 road sections (333 observations) from the LTPP database, pavement distress data were collected, including rutting, fatigue block cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, and ravelling with performance indicator data (PCI). The following can be concluded:

- The PCI values of the test section varied from ranging from 8 to 100 based on the different distress levels of the data.
- To ensure a safe driving experience, roads with PCI values of less than 40 should undergo maintenance. Therefore, the threshold PCI value of 40 should be maintained.
- For the wet freeze region, the PCI from MLR is dependent on the age, rutting, fatigue cracking, longitudinal cracking, transverse cracking, bleeding, and ravelling. Similarly, for the wet no freeze region, the PCI is related to age, rutting, fatigue cracking, longitudinal cracking, and transverse cracking.
- For the MLR, the R^2 value for wet freeze and wet no freeze was 86.8% and 89.3 %. The ANN has shown an increased R^2 of more than 99%. Additionally, the validation of the model is more effective for ANN than the MLR with a R^2 value of more than 98% and 77% respectively.
- Although ANN doesn't provide an equation for the prediction of PCI, but the model can correlate with the pavement damage. Alternatively, for comparison, the RMSE and MAE values were 7.195% and 5.616% for the wet freeze region, while for ANN, the minimum RMSE and MAE values were 0.44% and 0.44%. Therefore, ANN correlates better with PCI and distress in terms of error.
- Results illustrated that the MLR model with 10 independent variables was capable of predicting pavement performance for two climate regions i.e., wet freeze and wet no freeze, but the ANN models predicted the pavement condition with more accuracy and the lowest errors.
- Modelling of distress parameters helps evaluate pavement deterioration and pavement management systems. The present study uses nine distress parameters for predicting the PCI.

Future studies may include some more parameters like corrugation, slippage cracks, depression, polished aggregate and shoving to further improve these models.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors contribution statement

Conceptualization, A.A., U.H., A.H., S.A., and S.K; Data curation, A.A., and U.H; Formal analysis, A.A., U.H., A.H., and S.A.; Investigation, A.A. U.H., and S.K.; Methodology, A.A., U.H., A.H., and S.A.; Software, A.A., and U.H; Supervision, A.H.; Validation, A.A., S.A., and, S.K., and S.K.; Visualization, A.A.; supervision, A.H.; project administration, A.A., and U.H.; funding acquisition, S.A.; writing original draft preparation, A.A., and U.H.; Writing review & editing, A.A., S.A and S.K. All authors have read and agreed to the published version of the manuscript.

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