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Research Paper

Predicting a Pavement Roughness on the Basis of PCI Data

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Abstract

Pavement deterioration is a factor contributing to the higher roughness of the road and lower driving comfort in road trips. The pavement roughness measurement has long been an especially important topic to the practitioners. The pavement condition index (PCI) and the international roughness index (IRI) have been applied as two key measures of the quality and performance of the road pavement at the level of project or the road network. Since the pavement condition assessment across a road network by means of the PCI is highly expensive, the present research aims at estimating the PCI based on the IRI to save time and money while evaluating the pavement condition across a road network. For this purpose, we considered three IRI and PCI measurements over main suburban roads in a cold-weather area during a period of 6 years. Firstly, the independence of errors was controlled using the Durbin – Watson statistic, followed by evaluating the normality of the data using the Kolmogorov – Smirnov and the Shapiro – Wilk tests. In order to measure the correlation of the normal data, we used the Pearson's tests. Results of regression analysis between IRI and PCI showed that the best equation describing their association is a linear inverse model with an R2 = 0.992. A statistical comparison was made between the observed and predicted PCI values and model developed in the present research was further compared to similar research works, exhibiting acceptable agreement of the results.

Keywords: PCI, IRI, Regression Model, Road, Deterioration

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1. Introduction

Every day, millions of light and heavy vehicles travel over thousands of kilometers of road in Iran to transport goods and passengers. The passing traffic is among the main factors contributing to defects occurred to the pavement. Therefore, pavement assessment plays a key role in making proper decisions regarding the maintenance of the road network. So far, various indices have been proposed for assessing the pavement condition. [E. M. Ibrahim et al. 2020].

Generally categorized as either structural or performance-oriented, some of the most popular instances of these indices include Present serviceability index (PSI), pavement quality index (PQI), pavement distress index (PDI), pavement structural condition (PSC), pavement condition rating (PCR), structural condition index (SCI), riding comfort index (RCI), critical condition index (CCI), crack index (CI), pavement performance index (PPI), surface distresses index (SDI), overall pavement condition (OPC), urban distresses index (UDI), putting index (RI), distresses manifestation index (DMI), international roughness index (IRI) and pavement condition index (PCI) [Hafez et al., 2019; ODOT, 2004; Nam et al., 2016; Jannat and Tighe, 2015; Papagiannakis et al., 2009].

Given the available set of data, we considered the association between PCI and IRI for assessing the pavement performance. The road roughness has been defined as unevenness of the pavement surface with reference to a horizontal baseline, which leads to vibration of vehicle as it driven over the road. The IRI is one of the parameters used to measure the pavement roughness. It has been accepted as an international index of road roughness since 1982. [Zavagna, Khanal and Souliman, 2018].

This index is evaluated by dividing the height of uneven features over a predefined length of road by the distance of that segment, expressed in m/km or in/mi [Sayers et al., 1986].When a pavement is loaded, it is anticipated to exhibit an IRI in the range of 0.810 to 1.03 m/km, depending on its type, construction quality, and the path slope. [Smith and ram. 2016].

Manual measurement, response method, profilography, and lightweight and high-speed inertial profilometry have been used to measure the unevenness height for road roughness measurement. With the development of new technologies, even better methodologies have become available to capture the pavement roughness and the required standards for its acquisition and investigation have been already codified. [ASTM E1926 –08 (2021); AASHTO (2008); Du, Y et al. (2014); Sayers, M.W. and S.M. Karamihas (1998); Gillespie, T.D (1980); Akhter, M et al., (2003)].

PCI is a common criterion for assessing the pavement condition. This is a numerical index that ranges between 0 and 100 [Piryonesi and Tamber, 2020]. The value of PCI is related to defect type and intensity. These defects include alligator cracking, bleeding, block cracking, bumps and sags, corrugation, depression, edge cracking, joint reflection cracking, lane/shoulder drop off, long and trans cracking, patching and cut patching polished aggregate, potholes, railroad crossing, rutting, shoving, slippage cracking, swelling, weathering/reveling [Shahin, 2006; Huang, 2004; ASTM D6433, 1999].

IRI is usually acquired using special sensors attached to a vehicle, while PCI is evaluated through visual field visits or simply from images [Putra and Suprapto, 2018]. The abovementioned types of defect are recognized by the Road Maintenance and Transportation Organization (RMTO) of I.R. Iran and the relevant data has been recorded. Considering the difference in the evaluation method between the IRI and PCI, it has been recommended not to establish any relationship between the two indices. However, due to economic benefits of predicting PCI from IRI, prediction models have been proposed for relating these two indices [Arhin et al., 2015]. Although the LTPP dataset represents one of the largest and most popular sets of road performance data in the world, very limited research has been conducted on the correlation of PCI to IRI on the basis of this dataset [Piryonesi, 2019]. A research considered the correlation of the two indices based on the LTPP dataset using a total of 3954 records. The developed regression model ended up with an R^2 value of 0.31, which rendered undesirable. Once the data classification was reviewed and the required corrections were made, a regression model was presented as Equation (1), for which an R^2 value of 0.697 was obtained [Piryonesi and Tamber, 2020].

$$IRI = -0.045PCI + 5.024,\ R^2 = 0.697 \quad (1)$$

Various research works have been conducted on the PCI – IRI correlation. Based on a study on 6000 pavement segments across the Iranian rural road network using the pavement images and linear roughness profiles, a correlation was developed to link the PCI and IRI. Analysis of the results showed that an exponential regression model can best describe the studied data. The models of this study are expressed as Equations (2) through (4), leading to R^2 values of 0.999, 0.9984, and 0.9996, respectively. [Adeli et al., 2021].

$$PCI = -32.59\ln(IRI) + 132.93,\ R^2 = 0.999,\ 2.5 < IRI < 3.5\ (m/km) \quad (2)$$

$$PCI = -120.9\ln(IRI) + 240.61,\ R^2 = 0.9984,\ 3.5 < IRI < 5\ (m/km) \quad (3)$$

$$PCI = 1.4088(IRI)^2 - 28.426(IRI) + 154.75,\ R^2=0.9996,\ 5 < IRI < 8\ (m/km) \quad (4)$$

In another research, the data collected over a period of 2 years was used to develop PCI prediction models based on IRI in the District of Columbia. Results of descriptive statistics (i.e., average values) showed that the travel comfort was higher in express ways rather than main roads. Upon an analysis on the regression models, a statistically derived correlation was determined for expressing the association of IRI with PCI based on pavement performance and type classifications, leading to significant relationships with R^2 values in the range of 0.56 – 0.82. For instance, the regression models presented for the expressway and paved road are given as Equations (5) and (6) [Arhin et al., 2015]. Noteworthily, IRI is in (in/mi) in the following models.

$$PCI_{FWY} = -0.215(IRI_{FWY}) + 110.73,\ R^2=0.56 \quad (5)$$

$$PCIASP=-0.224(IRIASP) + 120.02,\ R^2 = 0.82 \quad (6)$$

In developing the HDM4 model, a number of effective defects were used to estimate the IRI, leading to significant correlations with acceptable R^2 values [Deori, 2019]. In the developing countries like Iran, appropriate data on PCI and IRI measurements are limited in many roads due to limitations of budget and equipment availability [Mahmoudzadeh et al., 2019].

In the present research, the data acquired over main roads in the Ardabil Province was used to study the IRI-PCI correlation.

2. Methodology

In this research, regression analysis was used for investigating the correlation of IRI to PCI. The regression is the most popular statistical technique for measuring and expressing the association of two quantities. We also used the Durbin–Watson statistic and the Kolmogorov–Smirnov and Shapiro–Wilk tests. The results were then compared to those reported in some previous research works. Finally, the SPSS software was utilized to present the proposed IRI – PCI model [Hoffmann, 2021].

3. Data Collection

The data used in this study was based on the pavement information acquired by the RMTO during 2014, 2017, and 2020 along the main roads in the Ardabil Province, Iran. For the purpose of this research, the main roads in this province include Bileh Savar – Pars Abad T-intersection, Razi-Aslandooz T-intersection, Meshkin Shahr-Ahar T-intersection, Ardabil-Garmi road, Nir-Ardabil road, Ardabil-Sarcham road, Khalkhal-Ardabil road, Ardabil-Astara road, Garmi-Bileh Savar road, Givi – Givi T-intersection, Khalkhal-Asalem road, Khalkhal-Givi road, Nir-Sarab road, and Pars Abad-Jolfa road. Out of the entire 800-km length of these roads, we considered a total of 200 segments with similar characteristics and which were not rehabilitated and/or coated during the three acquisitions. Among these segments, the ones where the geographic coordinates of the surveyed points coincided for the three surveys were selected. For example, Figure 1-a shows the coordinates of the IRI readings along the Khalkhal-Ardabil road in 2014 and 2017, and Figure 1-b shows the coordinates of the points over this road where IRI was measured in 2017 and 2020 [RMTO, 2020].

PCI assessment was performed using image processing to classify different parts of the studied road segment by defect type and intensity. Examples of pavement defects are shown in Figure 2. Outliers or erroneous data can affect the model development. Accordingly, apart from precising the data, we addressed geographic coordinate's errors, defective images, vision error, and low-quality images. Upon developing the model, a static relationship was found between IRI < 0.95 and PCI. That is, the PCI of all segments with IRI values below 0.95 was equal to 100. In this regard, we excluded all data points for which PCI was 100, and presented the model for 0.95 < IRI < 6.48.

Figure 1. (a) Coincidence of the road segments surveyed in (a) 2014 and 2017, and (b) 2017 and 2020

Figure 2. Images of defective pavement along Ardabil – Sarcham road

4. Analysis of Results

In a regression analysis, a basic assumption is the independence of error (i.e., the difference between actual values and the corresponding estimates). Should the error independence assumption be rejected and the errors are rather found to be correlated to one another, the regression analysis is no longer applicable. The Durbin – Watson statistic is usually used to measure the error independence. Indeed, a value in the range of 1.5 - 2.5 confirms the independence of errors [Oleh Anggraini and Siti wahyupa, 2019].

According to Table 1, the Durbin–Watson statistic for the data considered in this research was calculated at 1.909, confirming the error independence assumption and justifying the use of regression analysis. Normality of the data was tested using the Kolmogorov–Smirnov and Shapiro–Wilk tests with skewness and kurtosis controls. As reported in Table 2, we obtained skewness values of 0.713 and -0.844 for IRI and PCI, respectively. Moreover, the value of kurtosis was found to be -0.334 and 0.117 for IRI and PCI, respectively. The fact that all of the mentioned values fell in the range of -1.96 to 1.96 indicated the normality of the data [Arnastauskait˙e et al,2021].

Table1. Model summary

R	R Square	Adjusted R Square	Std. Error	Durbin-Watson
.996	.992	.992	.22493	1.909

As is shown in Table 3, the Kolmogorov – Smirnov test led to a p-value of 0.2 for both PCI and IRI. The corresponding values to the Shapiro–Wilk test were 0.058 and 0.089 for the IRI and PCI, respectively. The fact that these p-values were greater than 0.05 affirmed the normality of the data. Figure 3-a shows the histogram of the normal distribution for the linear regression model.

Table 2. Statistics

		IRI	PCI
N	Valid	473	473
	Missing	130	130
Mean		2.85	72.9
Skewness		.713	-.270
Kurtosis		-.334	-.117
Minimum		.96	11.60
Maximum		6.48	99.90

Correlation of the normal data was investigated using the Pearson’s test. As Table 4 suggests, the p-value was found to be smaller than 0.05 and the correlation coefficient over 473 points was evaluated at -0.996, indicating a significant yet inverse relationship between PCI and IRI at a confidence level of 0.95. The linearity of the data was checked graphically on a diagram. As Figure 3-b shows, the data was found to be linear.

Table 3. Tests of normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	p-value	Statistic	df	p-value
IRI	.086	473	.200	.933	473	.058
PCI	.067	473	.200	.931	473	.089

Table 4. Correlations

		IRI	PCI
IRI	Pearson Correlation	1	-.996
	p-value		.000
	N	473	473
PCI	Pearson Correlation	-.996	1
	p-value	.000	
	N	473	473

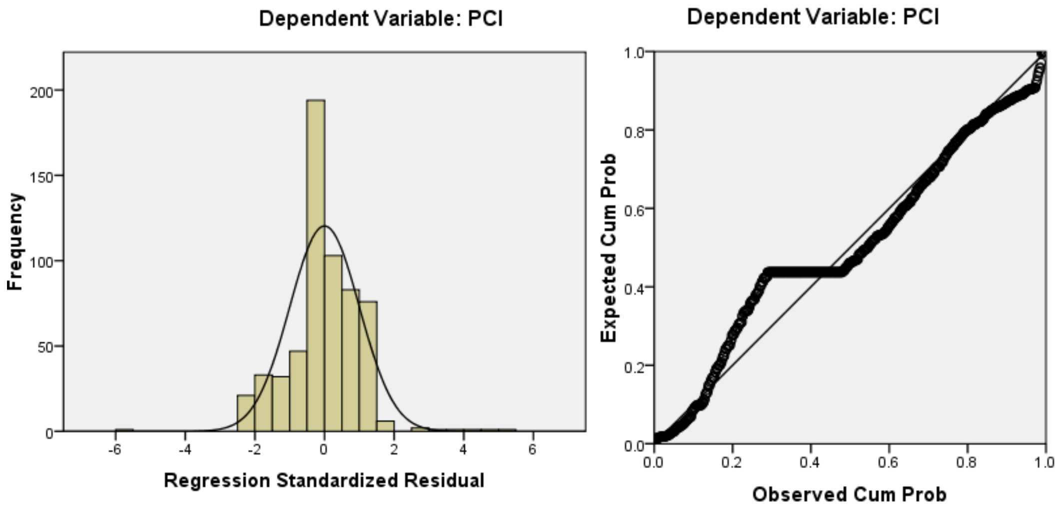

Figure 3. (a) Histogram of the normal distribution of the linear regression model, and (b) normal P-P plot of regression standardized residual

Various regression models have been used to improve the accuracy of predicting PCI from IRI data; these include linear regression, logarithmic regression, quadratic hyperbola regression, composite regression, power regression, and exponential regression. 70% of data was randomly selected and used for analyzing the model, with the remaining 30% used to validate the model. Table 5 presents the results of the regression models for predicting the PCI while Table 6 reports the output equations and correlation coefficients for different models. All models produced p-values below 0.05 Figure 4 demonstrates prediction performance of different regression models.

Table 5. Model summary and parameter estimates

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	p-value	Constant	b1	b2	b3
Linear	.992	5.769E4	1	471	.000	113.768	-14.335		
Logarithmic	.919	5.309E3	1	471	.000	108.512	-38.422		
Quadratic	.991	3.490E4	2	470	.000	110.503	-11.911	-.362	
Compound	.908	4.645E3	1	471	.000	139.834	.781		
Power	.758	1.478E3	1	471	.000	123.842	-.629		
Exponential	.908	4.645E3	1	471	.000	139.834	-.247		

Table 6. Models for predicting PCI from IRI

Equation	R Square	Model	IRI range
Linear	.992	PCI=113.768-14.335IRI	
Logarithmic	.919	PCI=108.512-38.22ln(IRI)	
Quadratic	.991	$PCI=-0.362(IRI)^2-11.911(IRI)+110.503$	0.96<IRI<7.238
Compound	.908	$PCI=139.834*0.781^{(IRI)}$	
Power	.758	$PCI=123.842*(IRI)^{-0.629}$	

Exponential	.908	$PCI=139.834*e^{(-0.247IRI)}$

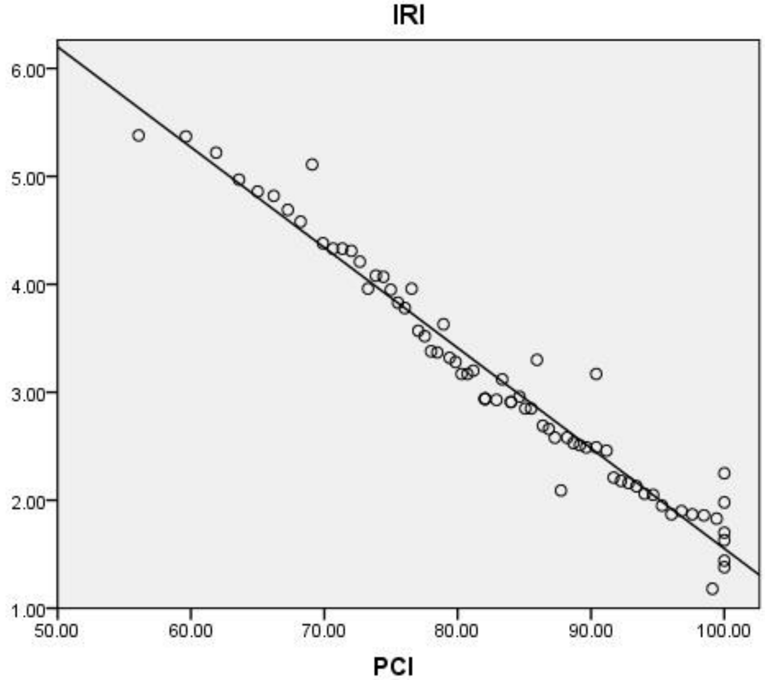

Figure 4. Prediction performance of the developed regression model

5. Model Selection

In this section. We begin by investigating the developed models for predicting the PCI, as listed in Table 6. We then select the best model based on the mentioned indices. Considering the normal distribution histogram (Figure 3) and performance of the regressive predictor models coupled with the values of the mean and standard deviation as well as closeness of the predicted values to the observed ones, as explained in the following, our analysis on the effect of the independent variable (*i.e.*, PCI) on the dependent variable (*i.e.*, IRI), the best-performing linear regression model was formulated as Equation (7).

$$PCI = 113.768 - 14.335IRI, \quad R^2 = 0.992, 0.96 < IRI < 7.238 \tag{7}$$

6. Discussion

Table 1 indicates a correlation coefficient of 0.992, meaning that PCI is correlated to IRI at a significance level of 0.99. We further obtained an R^2 value of 0.992, meaning that PCI covariates with the IRI in about 96% of cases. Equation (8) gives a K^2 coefficient of 0.01. This shows that some 1% of variations of IRI is not captured by the PCI.

$$K^2 = 1 - R^2 = 1 - 0.992 = 0.008 \tag{8}$$

Table 7 indicates a p-value smaller than 0.05 for the PCI, confirming it as a predictor of IRI. The negative value of the parameter B (B = – 0.093) indicates the inverse nature of the relationship between IRI and PCI. In such a case, the value of IRI decreases with increasing the PCI. The value of standardized beta in Table 7provides a measure of IRI variations per unit change in the standard deviation of PCI. That is, in this research, IRI decreases by 0.978 as the PCI increases by unity.

Table 7. Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	p-value	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	**(Constant)**	10.847	.200		54.315	.000		
	PCI	-.093	.002	-.978	-39.060	.000	1.000	1.000

As mentioned earlier, 30% of the entire data was selected on a random basis and used for validating the model. We further compared the predicted PCI values to the observed ones statistically and calculated the absolute percent deviation (APD) through Equation (9) to evaluate the robustness of the model.

$$APD = ([\text{Observed (PCI)} - \text{Predicted (PCI)}] / \text{Observed (PCI)}) \times 100 \quad (9)$$

Investigation of the model and substitution of IRI values to predict the PCI before comparing it with the observed PCI led to relatively low APD values. For instance, considering the observed PCI values of 85, 70 and 55, which corresponded to observed IRI values of 1.97, 3.07, and 4.18, respectively, we ended up with predicted PCI values of 85.53, 69.76, and 53.85, respectively. Applying Equation (3), standard deviation was found to be 0.3, 0.34, and 2, respectively. According to Table 2, minimum and maximum values of observed IRI were 0.96 and 6.48, respectively, while the minimum and maximum values of PCI were 11.6 and 99.9, respectively.

In the model obtained from this research (Equation 7), a relatively strong linear relationship was established between IRI and PCI. With this model, an IRI of 0.96 corresponds to a PCI value of approximately 100 while an IRI of 7.236 leads to a predicted PCI value of about 10. In the research that led to the model expressed as Equation (1), the model predicted a PCI of about 100 at an IRI of 0.524. Another piece of work introduced three models. The first and third models predicted PCI values of about 100 and 17.51 at IRI values of 2.5 and 8 m/km, respectively. In the study that ended up with Equations (5) and (6), the value of IRI was given in in/mi. Proposed for expressways, Equation (5) predicts a PCI of about 100 at an IRI of 49.9 in/mi (*i.e.*,0.79 m/km). Equation (6), which is designed for paved roads, a PCI of about 100 was predicted with an IRI of 89.3 in/mi (i.e., 1.41 m/km). The main distinction of the model presented in this research compared to similar models is the range of IRI in which they can operate. These ranges differ significantly, possibly because of the following reasons:

- Difference in the type of data: other studies have used long-term pavement performance (LTPP) data or the data coming from rural roads, differing with the source of data in the present research.
- Difference in road construction quality between different countries: the construction quality depends on the used material, tools, machineries, and standard regulations, making it behave differently in different countries.
- Difference in pavement defect type between different locations: Particular pavement defects tend to affect the value of PCI although they impose no effect on the IRI.

7. Conclusion

In this research, data from the Road Maintenance and Transportation Organization (RMTO) as well as field visits were used to formulate a correlation between IRI and PCI for the main roads in the Ardabil Province, Iran. For this purpose, we began by checking the error independence assumption using the Durbin – Watson statistic. The fact that the statistic fell in the range of 1.5 – 2.5 confirmed the independence of error assumption, justifying the applicability of regression analysis to IRI-PCI association. Next, normality of the data was tested and confirmed using the Kolmogorov – Smirnov and the Shapiro – Wilk tests with skewness and kurtosis controls. Once the data normality was assured, Pearson's test was applied and indicated an inverse correlation at 0.0978. The PCI-IRI regression model was established as PCI = 113.768 - 14.335IRI, $R^2 = 0.992$, $0.96 < IRI < 7.238$. Given the obtained p-value (0.000), statistical significance of the model was approved. Performing a comparative analysis between the model presented in this research and those in other studies and also considering the result of validation analysis in terms of deviation of predicted values from the measured ones, the properness of the model presented in the current study was approved. The outcomes confirmed an inverse association between IRI and PCI. The developed model is hence recommended for predicting PCI from IRI along roads of similar conditions in the Ardabil Province, and even in the entire country upon a refinement stage.

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