International Roughness Index Predictive Model for Rigid Pavements based on LTPP Data

توقع معاير الخشونه الدولي للرصف الصلب

By

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الخلاصة:

معاير الخشونة الدولي هو القياس الرياضي لنعومة سطح الرصف.فى هذه الدراسة تم بناء نموذج رياضي لتوقع قيم معاير الخشونه الدولي للرصف الصلب المنفصل باستخدام بيانات من مشروع اداء الرصف طويل الاجل. يتنبأ النموذج المقترح بقيم معاير الخشونة الدولي عن طريق عمر الرصف، القيمةالابتدائية لمعاير الخشونة الدولي، الهبوط، عدد الفواصل المتضررة، عدد الشروخ العرضية، التساقط و معامل التجمد).تقييم النموذج احصائيا يظهر تحسن ممتاز مقارنه بالنموذج السابق لدليل تصميم الرصف بالطريقةالفرضية الميكانيكية للتصميم حيث ان معامل الارتباط = 0.80 و الانحياز في القيم المتوقعة لهذا النموذج اقل منها مقارنه بالنموذج السابق ذكره.

Abstract

International roughness index (IRI) is the mathematical measurement of pavement smoothness. In this study, a regression model for IRI prediction for jointed plain concrete pavements (JPCP) was developed based on data from the Long Term Pavement Performance (LTPP) Project. A total of 327data points from 81pavement sections distributed all over the U.S. was used for the model development. The model predicts IRI as a function of pavement age, initial IRI, faulting, number of spelled joints, and number of transverse cracks, precipitation, and freezing index. The goodness of fit statistics of the model show excellent improvement over the previous model implemented in the Mechanistic-Empirical Pavement Design Guide (MEPDG). The model has a high coefficient of determination (R^2) of 0.80.In addition the bias in the predicted values of IRI was significantly lower compared to the previous MEPDG regression model.

1. Introduction

Ride quality and user comfort is always highly affected by longitudinal surface roughness. Roughness is defined as the deviations over the pavement surface compared to the designed surface grade [1]. The difference between the theoretical surface heights and actual surface heights in a longitudinal profile may occur as a result of the construction process, road use, distresses due to traffic loading and/or environmental conditions or of course a combination of all factors [2]. It was reported in the literature that 95 percent of pavement serviceability was related exclusively to the deviations of surface profiles [3]. International Roughness Index (IRI) is a statistical representation of surface roughness for just one wheel track. This mathematical simulation uses the quarter car system to generate an imaginary profile. As shown in Figure 1, the quarter car system is composed of two parts: a sprung mass representing the vehicle body (where the user is seated) and

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an unsprang mass representing the set of wheel/tire and half axle/suspension.

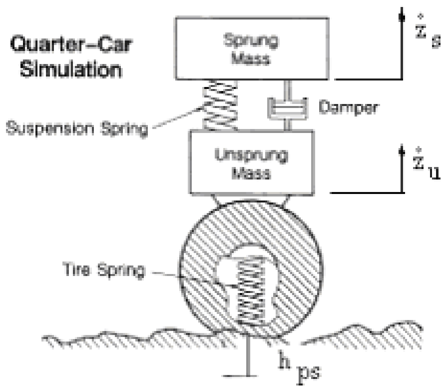


Figure 1. Quarter car simulation

The IRI represents the rectified average slope, or the absolute sum of the relative vertical displacement experienced by the user when driving a fictitious model car over a section (L) of the road at a constant speed of 80 km/h.

Rigid pavement is considered an important alternative while designing pavements to sustain heavier loads. Despite its higher initial cost compared to flexible pavements it usually has lower life cycle cost. Recently, the General Authority for Roads, Bridges, and Land Transport (GARBLT) in Egypt started to consider rigid pavement as a viable design option for roads with high percentages of trucks especially after the high rate of increase in bitumen prices as shown in Figure (2). Predicting IRI overtime is of great importance as it is considered one of the design criteria for rigid and flexible pavements in the new design methods such as the Mechanistic-Empirical Pavement Design Guide (MEPDG) [4]

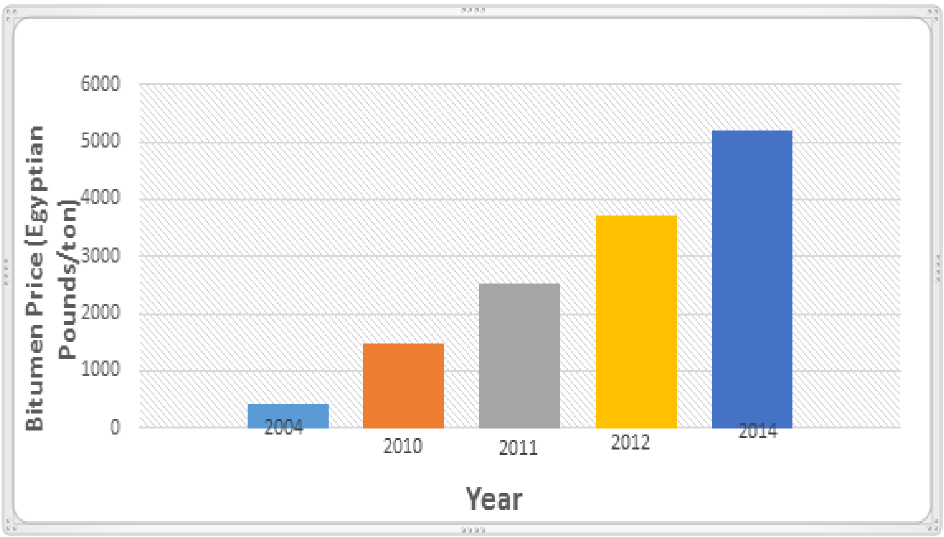


Figure (2): Change in Bitumen Price over the Last Ten Years

2-Research Objectives

The great majority of the current road network in Egypt is flexible pavements. Overloading combined with the inferior quality of materials and construction practices in Egypt lead to many distresses in the current roads especially rutting and fatigue cracking. In order to overcome this problem, GARBLT started to consider rigid pavements for the roads with high truck percentages. Thus, this study aims at developing a model for IRI prediction for rigid pavements.

3-Previous Studies

Many studies have tried to develop a rational model for predicting IRI values using either data from the Long Term

Pavement Performance (LTPP) or State Department of Transportation Management Data. Some studies correlated IRI with pavement distresses only whereas others correlated it to distresses, environmental conditions, and construction conditions. Many studies used regression models while few recent studies have used Artificial Neural Networks (ANNs) for the IRI predictions. Al-Omari, et al., [4] investigated the effect of individual distresses and a combination of distresses on pavement smoothness .FHWA Performance of Concrete Pavements [5] correlated IRI with a combination of joint faulting, spalling, and transverse cracks. The model yielded a coefficient of determination (R^2) of 0.61. The NCHRP 1-37A research project developed a regression model with R^2 =0.60 [6]. This model predicts IRI as a function of combination of pavement distresses, site factors and initial IRI using LTPP database. This study backcasted initial IRI values with unclear criteria. This study also discarded some LTPP sections from the database as well as some data points without showing the criteria doing this.Abd El-Hakim and El-Badawy[8] used the same database used for the development of the NCHRP 1-37A IRI model and developed an IRI predictive model using ANNs instead of regression analysis. The model yielded higher R^2 of 0.828 and showed bias. Bayrak, et al., [7] developed ANN model to predict IRI as a function of distresses, initial IRI, pavement age, faulting,AADT(Annual Average Daily Traffic) and transverse cracking with $R^2$of 0.84. A summary of the IRI predictive models for JPCP found in literature is shown in Table (1)

Model Reference	Model Structure	Data Used	Goodness of fit	Data points
5	IRI^2= 99.59 + 2.6098*FaulTT + 2.2802*T-crack^3+ 1.8407*Spall	LTPP	R^2=0.61	N.A.
4	IRI = 1.471 + 0.2794*F	LTPP	R^2=0.50	N.A.
6	IRI = IRII+ 0.013*TC + 0.007*SPALL + 0.005*PATCH + 0.0015*TFAUL + 0.4S*FT	LTPP	R^2=0.60	188 data points
8	8 inputs, 2 hidden layers with 24 and 12 neurons and 1 output layer (8-24-12-1)	LTPP	R^2=0.828	188 data points
7	7inputs, 1 hidden layer,10 neurons and 1 output layer(7-10-1)	LTPP	R^2=0.84	264 data points

Table (1) Summary of Literature IRI Predictive Models for JPCP.

Where, IRI = International Roughness Index, in/mile, FaulTT = total accumulated joint faulting, in/mile, T-crack = amount of transverse cracking, number of cracks per mile,Spall = percentage of joints spalled , IRI1= initial smoothness measured as IRI, m/km, TC = percentage of slabs with transverse cracking (all severities),SPALL = percentage of joints with spalling (all severities),PATCH = pavement surface area with flexible and rigid patching (all severities), percent,TFAULT = total joint faulting cumulated per km, mm,SF = site factor= Age*(1+FI)*(1+P200)/1000000,Age = pavement age in years,FI = freezing index, ^{o}C days,P200 = percent subgrade material passing the 0.075-mm sieve.

3-Data Collection

The Long-Term Pavement Performance (LTPP) program started in 1987, as part of the Strategic Highway Research Program (SHRP), a 5-year applied research program funded by the 50 states and managed by the Transportation Research Board (TRB). [10]. With the goal of extending the life of pavements through investigation of the long-term performance of various designs of pavements (as originally constructed or rehabilitated) under various conditions, the following objectives were established for LTPP:

1. 1-Evaluate existing design methods

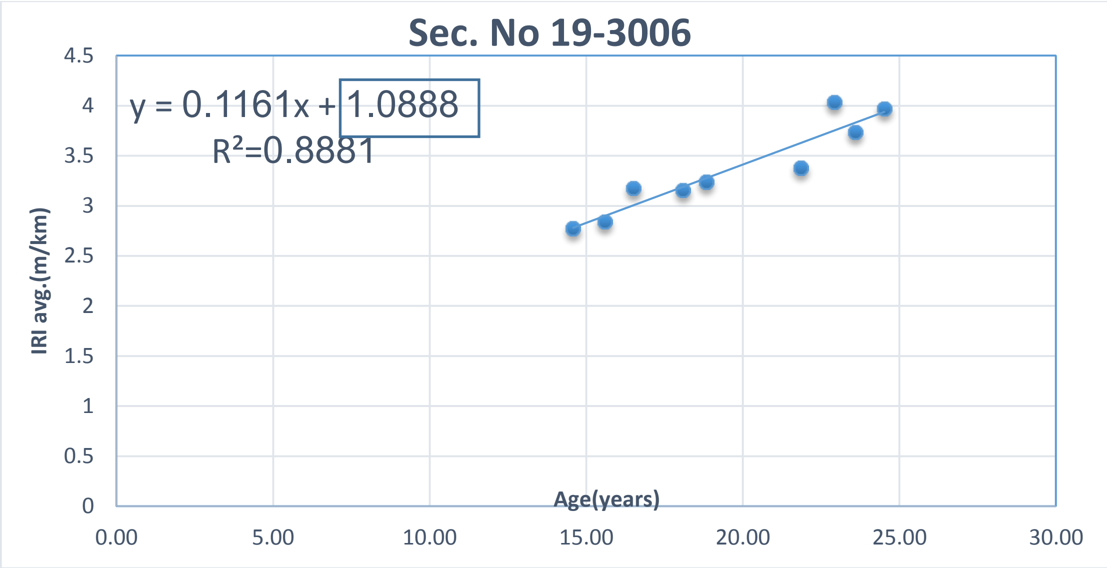
2. Develop improved design methodologies and strategies for the rehabilitation of existing pavements.
3. Develop improved design equations for new and reconstructed pavements.
4. Determine the effects of loading, environment, material properties and variability, construction quality, and maintenance levels on pavement distress and performance.
5. Determine the effects of specific design features on pavement performance.
6. Establish a national long-term pavement database.

In this study, 81 LTPP JPCP pavement sections distributed all over the United States with 327 data points were used to develop a predictive model for the IRI. It should be noted that the NCHRP 1-37A IRI model was based only on 188 points. The collected data includes one dependent variable which is the IRI and seven independent variables which are theinitial IRI, age, faulting, number of spalled joints, number of transverse cracks,freezing index, and precipitation. Each variable was collected from a specific module and table form LTPP DATAPAVE online

Some data were in a format that are ready to use and some other data needed some processing. As the literature studies pointed out the significant influence of the initial IRI (IRI directly after construction) on the IRI at any time, it was felt important to include this parameter in the proposed model. The LTPP data does not have the intimal IRI as most of the LTPP sections were built long time ago before IRI was used as a measure of pavement roughness. Thus, the initial IRI values were backcasted using the following procedure:

1. Collect available IRI data from LTPP database at different ages from (MON_PROFILE_MASTER) table.
2. Collect maintenance and rehabilitation history of different sections from (MNT_IMP) and (RHB_IMP).
3. Evaluate the effect of each type of maintenance and rehabilitation on the values of IRI for all sections
4. Discard the values of IRI after maintenance and rehabilitation action that caused a significant reduction in the IRI value
5. Evaluate different mathematical model forms (e.g. linear, exponential, logarithmic and polynomial) for back-casting initial IRI where age in years was considered the independent variable and IRI in m/km was the dependent variable. It is found that, the linear model was the best mathematical form expressing the IRI with age for the available data.
6. Back-cast initial IRI values for all pavement sections following the above criteria as initial IRI is the value of IRI at age=0 and as an example section with state code of 19 and SHRP ID of 3009 is shown in figure (3) .

This procedure was used for all the 81 LTPP JPCP sections and initial IRI was estimated. The LTPP data tables used for the collection of data for the model development are summarized in Table 2. Another challenge and may be a weak point in the LTPP data base is that the profile date in which IRI is measured usually differs from the distress date. In order to overcome this problem, the same backcasting equation used for the initial IRI estimation for each section was also used to estimate the IRI value at the same date of the distress recording. Finally,data was tabulated to be used for the model development.Table3 summarizes the descriptive statistics of the collected data.



Figure(3)Initial IRI backcasting

Table (2) Definition of used data variables

Variable	Definition	Data Table
SHRP ID	Stratagic Highway Research project specific ID for each section	INV_AGE
State Code	Specific code for each state	INV_AGE
IRI	Average wheel path IRI taken as average of 5 to 10 wheel path IRI recordings at each date	MON_PROFILE_MASTER
Traffic open date	The date in which section is opened to traffic	INV_AGE
Constructio n number	A number increment indicates that a maintenance action is done.	MON_PROFILE_MASTER
Freezing Index	Average freezing index in "°C"	CLM_VWS_TEMP_ANNUAL FREEZE_INDEX_YR
Precipitation	Average annual precipitation in "mm"	CLM_VWS_PRECIP_ANNUAL
Faulting	Total joint and crack faulting in mm/km	MON_JPCP_REV_FAULT
Spalling of joints	Total number of spalled joints with all severities	MON_DIS_JPCC_REV
Transverse cracks	Total number of transverse cracks with all severities	MON_DIS_JPCC_REV

Table (3) Descriptive statistics of variables

Variable	Minimum	Maximum	Mean	Range	Stamdard deviation
Initial IRI (m/km)	0.66	2.07	1.28	1.41	0.019
Age (years)	0.1	36.92	17.47	36.82	0.40
Faulting mm/km	0	1390.84	191.39	1390.84	243.6
Trans cracks number	0	21	0.82	21	0.14
Spalled joints number	0	34	2.27	34	0.29
Precipitation(mm)	146.5	1760.38	901.63	1613.88	23.4
Freezing Index "Celisus degree"	0	1565.2	280.01	1565.2	20.44

4-Model Development

In this study, a multiple linear regression model was developed with one dependent variable which is IRI and eight independent variables which are faulting, transverse cracks with all severities, spalling of joints also with all severities, age, initial IRI, precipitation, and freezing Index.,. These variable were selected after careful review of the literature. In addition, the influence of the each of these factors on the IRI was also studied. The model was developed using the linear optimization technique based on the least square method. The model was then statistically evaluated to assure the quality of model and study the significance of each factor. The proposed model is shown in Equation(1):

$$IRI=0.142+0.78(IIRI)+0.0132(age)+0.000152(Fault)+0.018(Tcrack)+0.014(Spall)+0.000109(perc.)+0.000072(FI) \quad (1)$$

Where, IRI=predicted IRI in m/km;IIRI=initial IRI value in m/km;age=pavement age in years;fault = total faulting mm/km;Tcrack=total number of transverse cracks;Spall=total number of spalled joints;perc.= annual average precipitation in mm;FI=freezing index in degrees Celsius.

LTPP measured versus IRI predicted using the proposed model is shown Figure 4. The data in this figure along with the goodness of fit statistics shown in Table (4) indicate excellent prediction accuracy.

Table (4) Regression statistics

Regression statistics	
Observations	327
Multiple R	0.892
R Square	0.803
Adjusted R Square	0.798
Standard Error (Se)	0.164
Se/Sy	0.31

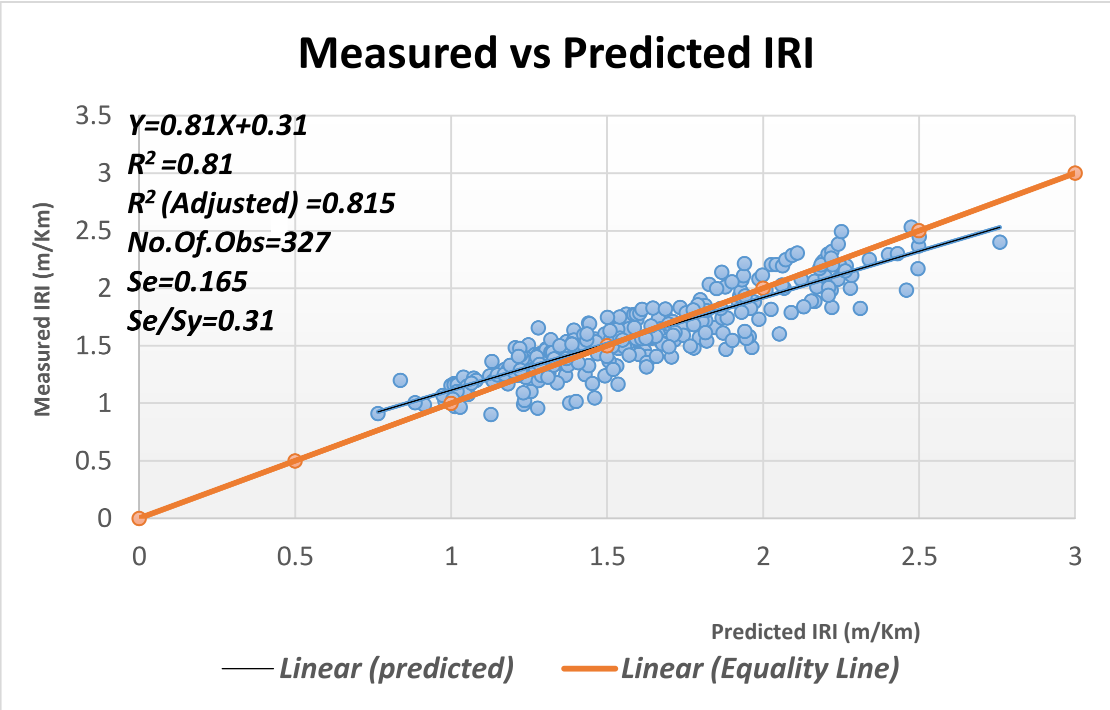


Figure (4) Measured vs predicted IRI

The bias in the model predictions was also evaluated statistically. A linear regression on the measured and predicted IRI was conducted and the following hypothesis tests at a significance level of 5 percent (α= 0.05) were performed.

Hypothesis 1: Determine whether the linear regression model developed using measured and predicted IRI has an intercept of zero by testing the following null and alternative hypotheses Ho: Model intercept = 0, HA: Model intercept ≠ 0. [9]

A rejection of the null hypothesis (p-value < 0.05) would imply the linear model had an intercept significantly different from zero at the 5 percent level of significance. In other words, the model produces biased predictions especially at the very low values of IRI.

Hypothesis 2: Determine whether the linear regression model developed using measured and predicted IRI has a slope of unity by testing the following null and alternative hypotheses:

Ho: Model slope = 1.0, HA: Model slope ≠ 1.0. A rejection of the null hypothesis (p-value < 0.05) would imply that the linear model has a slope significantly different from 1.0 at the 5 percent level of significance. In other words, the model results in biased predictions especially if used outside the range of measured rutting used for the calibration.

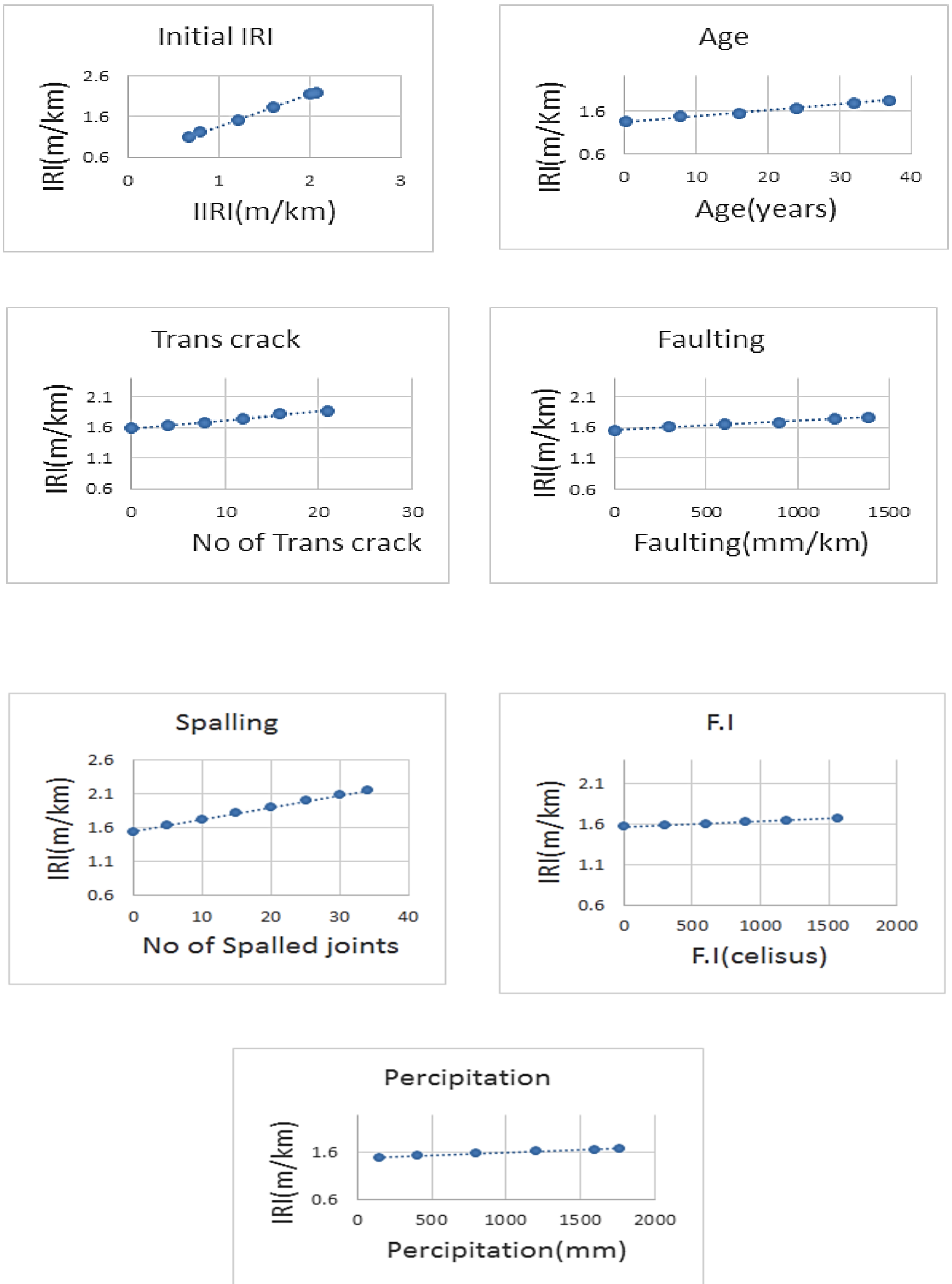
A rejection of any of the two null hypotheses (p-value < 0.05) would imply that model results in biased predictions. If the model passed all three hypotheses tests successfully, the model predictions are not biased.The results of the conducted hypotheses tests are summarized in Table 4. The results indicate that the model is not biased statistically.

Table(4) Statistical Comparison of Measured and Predicted IRI

Hypothesis	Degrees of freedom	Coefficient	Standard Error	T-stat	P-value
Ho:Intercept=0	1	0.31	0.0443	4 E -14	0.41
Ho:Slope=1.0	1	0.81	0.0273	3.24 E-14	0.21

5-Sensitivity Analysis

In order to assess the influence of each variable in the model on the predicted IRI, a sensitivity analysis was conducted. The sensitivity analysis was performed by changing each variable in the proposed between its minimum and maximum values while keeping the other variables fixed at the mean value based on the data used. Figure (5) shows the sensitivity analysis results for all variables. The sensitivity analysis shows that IRI is strongly sensitive to the variation of initial IRI and distresses and less sensitive to precipitation and freezing index



Fig(5) Sensitivity Analysis

6-SUMMARY and Conclusions:

Predicting IRI as a mathematical representation of roughness and ride quality is of a great importance. In this study 327 data recordings from 81 LTPP JPCP pavement sections were used to develop a regression model to predict IRI as a function of initial IRI, age, faulting, transverse cracks, spalling, precipitation, freezing index. Bias of the model was checked statically using hypothesis testing. A sensitivity analysis was conducted to show the effect of each variable. Following are the conclusions drawn from this research:

1-The developed regression model yielded a high coefficient of determination (R^2) of 0.8 with (Se/Sy) of 0.31 which yielded better goodness of fit compared to the previous MEPDG model (coefficient of determination (R^2) of 0.6 and (Se/Sy) of 0.643).

2-The hypothesis testing showed that bias in the predicted values of IRI was significantly lower compared to the previous MEPDG regression model.

3-The sensitivity Analysis showed that Initial IRI is the most significant factor affecting IRI values over time then age and distresses and finally environmental factors including freezing index and precipitation.

4- It is recommended that LTPP database authority measures IRI at the same time of distress

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