International Journal of Pavement Engineering

ISSN: 1029-8436 (Print) 1477-268X (Online) Journal homepage: https://www.tandfonline.com/loi/gpav20

Applicability of smartphone-based roughness data for rural road pavement condition evaluation

R. M. K. Sandamal & H. R. Pasindu

To cite this article: R. M. K. Sandamal & H. R. Pasindu (2020): Applicability of smartphone-based roughness data for rural road pavement condition evaluation, International Journal of Pavement Engineering, DOI: 10.1080/10298436.2020.1765243

To link to this article: https://doi.org/10.1080/10298436.2020.1765243

Published online: 22 May 2020.

INTERNATIONAL JOURNAL OF PAVEMENT ENGINEERING
https://doi.org/10.1080/10298436.2020.1765243

Applicability of smartphone-based roughness data for rural road pavement condition evaluation

R. M. K. Sandamal and H. R. Pasindu

Department of Civil Engineering, University of Moratuwa, Katubedda, Sri Lanka

ABSTRACT

Rural roads play a pivotal role in facilitating connectivity for the rural communities by providing access for their economic and social needs. Due to lack of funding and other resources, maintenance decision making is often done in an ad-hoc and subjective manner. Moreover, the inability to collect extensive data as needed to run most pavement management systems and technical expertise required has resulted in the low usage of such systems by local road agencies. Therefore, there is a need to develop a cost-effective, simplified approach for network-level pavement condition evaluation to assist in pavement maintenance management. The study explores the applicability of smartphone-based roughness data to assess the pavement condition of rural roads, and it is compared with the results from a Class III type roughness measurement equipment. Result show it has good correlation, which suggests it has sufficient accuracy when compared to the conventional roughness measurement methods. Furthermore, it is established that roughness results accurately represent the presence of pavement distresses and the overall pavement condition in the rural roads that are considered in maintenance decision making. The findings from the study would provide a cost-effective pavement condition data collection method that can be adopted for network-level condition evaluation in low volume roads.

ARTICLE HISTORY
Received 13 December 2019
Accepted 1 May 2020

KEYWORDS
roughness; low volume roads; pavement management systems; smartphone-based roughness data

Introduction

Rural roads play a pivotal role in facilitating connectivity for the rural communities providing access to markets, education, health, and other social needs. The condition of the pavements is generally poor, resulting in an increase in transport costs to those in rural areas. Therefore, these roads must be maintained at a satisfactory condition to meet the transport demands of the rural communities. Several constraints are faced by local agencies who maintain the rural road networks; lack of technical expertise, consistent funding and ad-hoc or subjective decision making are amongst the major impediments to ensure the road network is maintained efficiently and cost-effectively (Moazami *et al.* 2011, Mathew and Issac 2014). Conventional pavement management systems are data-intensive and require a reasonable level of technical expertise to collect, analyse the data (Asian 2018) collection of the several types of data relating to pavement distresses is time-consuming and costly, especially when done at a network level. As a result, the pavement management systems are not adopted by the local agencies. Alternative techniques must be identified to evaluate the pavement condition, at the same time it must be cost-effective and less time-consuming. Pavement roughness is globally accepted as a suitable parameter to represent the pavement condition, especially for network-level condition assessment. Furthermore, there are novel techniques such as smartphone-based roughness data collection which has made it cost-effective and less time-intensive (Gamage *et al.* 2016). However, it must be established whether the pavement roughness value would accurately represent the condition of the rural roads considering its roadway characteristics and the distresses commonly observed in such roads. The maintenance decisions making based on the roughness data should be consistent with the maintenance decisions that would have been made based on the distress data for that road segment to ascertain that roughness data is a suitable metric for the condition evaluation. Also, the accuracy of the roughness data from the smartphone app should be established in comparison to the conventional roughness measurement methods such as the bump integrator.

The main objective of this study is to evaluate the applicability of smartphone-based roughness measurement in terms of the International Roughness Index (IRI) as a condition evaluation parameter for rural roads. The scope of the proposed study includes the following components,

- Examine the suitability of smartphone-based IRI values in comparison to a response type IRI measurement.
- Identify the visible distress in rural roads and examine their relationship with IRI in different stages of the pavement life.
- Evaluate the applicability of IRI as a predictor of pavement condition index (PCI).

Pavement condition evaluation in rural roads

Pavement condition evaluation typically consists of four aspects, i.e. distress condition evaluation, pavement roughness

CONTACT R. M. K. Sandamal pasindu@uom.lk

measurement, skid resistance and structural capacity evaluation (Hass *et al.* 1994). Various composite indicators and user perception-based rating methods were developed to evaluate pavement condition, such as pavement condition index (PCI), present serviceability rating (PSR), roughness index (RI), remaining service life (RSL) etc (Shah *et al.* 2013). Thube *et al.* (2007) derived the present serviceability index (PSI) and PCI based composite pavement deterioration models for low volume roads in India. A complex prioritisation index called Modified Maintenance Priority Index (MMPI) is developed to overcome the issues with existing maintenance prioritisation methods for low volume roads (Avinash *et al.* 2014). The index is a combination of deflection and roughness measurement primarily while introducing maximum permissible value. In addition, traffic volume, rutting and fatigue failures are considered in developing the index. A quick and simple rural road condition measurement method based on a hierarchical structure was developed by Beckemeyer (1995), which also incorporates traffic safety and drainage condition in addition to the existing pavement condition evaluation methods, into the decision making process.

Ravelling, pothole, fatigue and longitudinal cracking, edge break and rutting are the types of distresses that are commonly observed in rural road networks according to a study on rural roads by Mane *et al.* (2016), these were used to develop guidelines for distress rating system.

Quantitative methods are still useful for assessing and rating the road conditions based on defined severity levels and extents. As illustrated by Nkomo *et al.* (2016), if the selected distresses had both depth and width less than 15 cm, the severity was classified between 0–4 and if any measurement more than 15 cm then it was given the rating of 5. An extent is defined by percentage area classified as A-E with extent less than 5% is considered as A and greater than 80% as E. Based on the value of extent*severity, the treatment is applied on pavement surface by addressing distresses such as pothole, rutting and loose materials (Aleadelat *et al.* 2018).

Further, the Analytical Hierarchy Process (AHP) used as a multi-criteria decision tool to prioritise maintenance strategies (Mane *et al.* 2016, Muthuma *et al.* 2016, Nkomo *et al.* 2016). The results from AHP (Nkomo *et al.* 2016), indicated that unevenness, skid resistance, bearing capacity are the indicators while ravelling, rut depth, potholes are the type of distresses which are the best representatives in evaluating pavement condition in the rural road network. Based on the defined weightage and rating for each distress type, pavement performance index (PPI) developed to evaluate pavement condition which is shown in Equation (1) (Tawalare and Raju 2016).

$$PPI = \sum_{i=0}^{n} (W_i \times R_i) \tag{1}$$

Where *PPI* is the pavement performance index; R_i is the rating of each deterioration parameter; W_i is the weightage of each deterioration parameter

Flexible pavement condition of local roads assessed by developing ride comfort rating at posted speed with three categories such as surface defects, surface deformation and cracking (Gunasoma and Pasindu 2016). In addition, distress manifestation index (DMI) which is a visual comparative method is introduced to asses road segments. Base failure index (BCI) along with PCI is investigated rural asphalt road condition based on matter element analysis (Zhang and Gao 2017). The analysis process is divided into two parts as establishing matter-element and establishing a classical segment field. Establishing the matter-element field is described evaluation levels with BCI and PCI as shown in Equation (2).

$$R_n = \begin{pmatrix} M & C_1 & X_1 \\ & C_2 & X_2 \\ & . & . \\ & . & . \\ & C_n & X_n \end{pmatrix} \tag{2}$$

Where R_n is the matter element; C_1 is the pavement surface condition index (PCI); C_2 is the base failure index (BCI); *M* is the evaluation levels either excellent, good, middle, bad or poor; *X* is the value of things *M* about the characteristic *C*, that is, PCI and BCI on five levels of the score range

Relationship between roughness and distress condition

The relationship between surface distress and roughness in low volume roads provides useful information for pavement maintenance management. The relationship between different types of distresses on roughness becomes significant at different roughness threshold values. For example, pothole and cracking increase the overall pavement roughness at 0.25 and 0.124 m/km respectively for 1% increase the distress extent for low volume roads with IRI values above 5 m/km (Pogson 2013). Similar observations were made on the effect of ravelling on IRI increasing of asphalt concrete pavements in different highway segments (Zhang and Gao 2017).

Pavement roughness development is a result of distresses progression which is modelled in HDM-4 software (Morosiuk and Michael 2004) as shown in Equation (3), which identifies the significance of distresses such as cracking, rutting, potholes to roughness.

$$\Delta RI = K_{gp} + \Delta RI_s + \Delta RI_c + \Delta RI_r + \Delta RI_t + \Delta RI_e \tag{3}$$

Where K_{gp} is the calibration factor of general surface roughness development; ΔRI is the gradual increase of pavement surface roughness; ΔRI_s is the structural pavement deterioration; ΔRI_c is the deterioration due to cracking; ΔRI_r is the deterioration due to rutting; ΔRI_t is the deterioration due to pothole; ΔRI_e is the deterioration due to climate effects

Several studies are conducted to investigate the relationship between IRI with distresses and applicability as a pavement condition evaluation parameter is shown in Table 1. The results indicate that roughness and the condition of the main distresses have a good correlation. This suggests that the roughness values of pavement would assess the pavement condition similar to that made by a pavement engineer. Especially, for the network level pavement condition evaluation, this would be sufficient for maintenance decision making.

Table 1. Summary of studies conducted to evaluate the relationship between IRI and distresses

Model / Analysis method	Method of IRI measurement	Key findings
Saudi Arabia (Mubaraki 2016)/ Multivariable regression analysis	Automatic Road Analyzer (ARAN) system consist of accelerometer and roughness laser	R^2=0.3 for functional model Raveling, cracking shown good significant Rutting is shown low significant Model-1: IRI=4.498 + 0.0096CRA+0.0083RUT+0.0067RAV Model-2: IRI=3.58 + 0.0077CRA+0.0054RAV Where: CRA-cracking%; RUT-rutting%; RAV-ravelling%
Indian (Prasad *et al.* 2013) / Multiple-linear regression	Bump integrator	R^2=0.66, Mean Absolute Percentage Error (MAPE) = 9.8% High severity edge cracking, High severity alligator cracking, Medium severity pothole predominant *IRI_D (m/km) = 3.23 + 0.318ACL + 1.205ACH + 0.120L/T CL + 0.041L/T CM + 0.023RH + 0.698PL + 1.189PM + 0.125PAH + 3.00ECH + 0.162EBL + 0.269EBM + 0.145EBH
Turkey (Kirbas 2018)/ Multivariate Adaptive Regression Splines (MARS) approach	Image processing system using high-resolution (HD) cameras	R^2=0.74 Alligator cracking, depression and patching were shown higher influence on increasing IRI up to 500% The mathematical model is developed adding 67 basic functions, with 29 independent variables.
Taiwan (Lin *et al.* 2003) / Back-propagation neural network methodology	Automatic Road Analyzer (ARAN) system consist of accelerometer and roughness laser	R^2=0.89 Severe pothole, digging/patching, rutting shown highest correlation Bleeding, road level is shown least correlation Sigmoid transfer function = 1/ [1 + exp(-x)] Where: x- distress variable with severity level
Iran (Yeganeh 2017) / Regression analysis	A smartphone which embedded accelerometer sensor and road surface profiler	Good correlation (r=0.91) between IRI measured by smartphone and traveller's opinion (functional condition) IRI = 4.19RMS+1.73 Where: RMS - root mean square of acceleration data

*IRI_D refers to IRI due to distress; ACL & ACH refers to low & high-level alligator cracking % area; L/T CL & L/T CM refers to low & medium level longitudinal/transverse cracking in meters; RH refers to high-level ravelling in % of the area; PL & PM refers to low & medium level potholes % of the area; PAH refers to high level patching % of the area; ECH refers to high-level edge cracking in meters; EBL, EBM & EBH refers to low, medium & high-level edge break in meters

The roughness values of the pavement can be also be related to the overall pavement condition as shown in Equation (4), which was developed by using long term pavement performance (LTPP) data gathered from 20 pavement sections in 11 states in the USA (Park *et al.* 2007).

$$PCI = K_1(IRI)^{K_2} \tag{4}$$

Where *PCI* is the pavement condition index; *IRI* is the international roughness index in-unit m/km; K_1 and K_2 are the constant values 2 and −0.481 respectively

Roughness is also used as a pavement functional condition measurement which describes the composite behaviour of distress condition by capturing the relevant distresses. PCR is the overall global functional condition indicator shown in Equation (5), which consists of PCI and RCI (roughness condition index) shown in Equation (6), which provide better interpretation of the condition of roads in rural areas (Pantuso *et al.* 2019). The use of RCI improved the ability to predict the functional condition, validating pavement requirements on the network level. It can be used as the first screening tool to identify the most suitable treatment on a particular pavement section.

$$PCR = 0.6PCI + 0.4RCI \tag{5}$$

$$RCI = 253.67e^{-0.459IRI} \tag{6}$$

Where *PCR* is the pavement condition rating

Pavement condition score (PCS) is a combination of distresses pothole, rut and cracks with defined weightage (Park *et al.* 2007). PCS index has shown a strong correlation of 0.79 with roughness, which provide evidence that roughness is a good substitute for visual condition measurements as shown in Equation (7).

$$PCS = 83.792 - 5.226IRI \tag{7}$$

Where *PCS* is the pavement condition score

The discomfort due to poor road sections with higher distress levels can be measured by IRI accurately. The effect of vibration can be determined by the verticle acceleration using the frequency-weighted root mean square (RMS). The study conducted by Cantisani and Loprencipe 2010, showing that there is a strong correlation of 0.9 between IRI and vertical weighted RMS acceleration (a_{wz}) as shown in Equation (8).

$$a_{WZ} = 0.222IRI \tag{8}$$

Where a_{wz} is the vertical weighted root mean square acceleration measured in unit m/s^2

Smartphone-based roughness evaluation

Roughness evaluation using a traditional Class I type equipment such as laser profilometer is not generally adopted in low volume roads, especially in developing countries due to the high cost of the equipment and the difficulties to use on the narrow roads. Even Class III type measurement equipment such as bump integrator is not commonly available in local agencies. Therefore, several researchers have investigated the use of smartphone-based roughness measurement methods (Tai *et al.* 1998, Abiola *et al.* 2014, Bisconsini *et al.* 2018).

Smartphones-based roughness measurement leverage on the accelerometers inbuilt in smartphones to detect the vertical acceleration and the apps have been developed to estimate the roughness values based on the readings. 3-axis accelerometer, gyroscope and a Global Positioning System (GPS) are

Table 2. Summary of results on smartphone-based roughness measurement.

Data collection instrument	Vehicles used	Measured IRI range	Speed of measurements	Key findings
Smartphone model in HTC with a video camera (Gamage *et al.* 2016)	Toyota Hilux 4WD cab	1.5m/km-10m/km	20kmph-60kmph	Correlation between IRI and resultant acceleration is range from 0.55–0.75 for different speed of the vehicle. No significant variation with change in the speed of the vehicle
Smartphone model in Samsung Galaxy S5 mini with accelerometer and GPS (Bisconsini *et al.* 2018)	A passenger car	1m/km-16m/km	20kmph-60kmph	Correlation of 0.97–0.99 with roughness measurements of rod and level method Speed of measurement does not affect significantly on roughness measurements
Two Android smartphones and GPS logger with a video recorder (Douangphachanh and Oneyama 2013)	Toyota VIGO pickup truck and Toyota Camry car	1.5m/km-16m/km	10kmph-80kmph	Correlation of 0.67–0.75 The linear relationship is a better representative The relationship is considerably strong when speed is less than 60kmph Less importance on vehicle type and device
Samsung Galaxy S8 with GPS (Buttlar *et al.* 2018)	Chevy Traverse LT 2015 (Car)	Up to 3.6m/km	30kmph-100kmph	Found a sound correlation of 0.8–0.85 between smartphone IRI and PCI
Smartphone application with GPS (Yeganeh *et al.* 2017)	A passenger car	2m/km-12m/km	20kmph-50kmph	Correlation of 0.76 between IRI vs RMS (root mean square) Travelers opinion confirmed the applicability of smartphone IRI with a correlation of 0.81

used to measure road roughness (Kirbas 2018). There are several commercially developed software such as Roadroid App (Islam *et al.* 2014) that can be used to evaluate pavement roughness.

Moreover, distress detection methods have also been developed to identify distresses. Based on the amount and wavelength, distresses such as rutting, irregular patches, corrugations and potholes on the pavement surface can be captured accurately (Abiola *et al.* 2014, Buttlar and Islam 2014).

To assess the validity of smartphone-based roughness measurement, estimated IRI from the smartphone app and the values compared with rod and level measurement areas (Yeganeh *et al.* 2017). The results indicated that its applicability is high in pavement management systems for network-level evaluation since the variation is low as 3%-6% while Pearson correlation (R) is high as 0.97% to 0.99%. There are several studies are conducted to validate the applicability of smartphone-based roughness measurement for condition evaluation and summary of the key finding of previous researchers are shown in Table 2.

The results of these studies done to validate the applicability of smartphone-based roughness measurements provides sufficient evidence on suitability for rural roads. The accuracy of the results shown to have less variability with the type of vehicle (Roadroid 2019), the smartphone model (Abiola *et al.* 2014) and the speed of the vehicle for data collection (Eriksson *et al.* 2008, Douangphachanh and Oneyama 2013).

Pavement condition evaluation of rural road network

Introduction to the study area

95 rural roads with a total length of 434 km are selected, including a single lane and two lanes carriageway with a maximum width of road limiting to 6 m. All the study road segments are constructed using asphalt concrete while all the roads are in rolling and flat terrain. The summary of road inventories from the selected road network is shown in Table 3.

Mixed traffic composition is observed in the road network with 88% of the traffic composition consist of three-wheelers and motorcycles and very low heavy vehicle flow (6%) in the majority of the roads. The summary of traffic characteristics in the road network is shown in Table 4.

Relationship between bump integrator IRI and smartphone-based roughness measurement

The validity of smartphone-based roughness measurement is evaluated by comparing with pavement roughness measured by bump integrator (Douangphachanh and Oneyama 2013) which is calibrated through the Z-250 walking profilometer using 78 roads from the rural road network. Roadroid mobile application (version 2.4.1) (Roadroid 2019) was used in data collection (Islam *et al.* 2014) using a tri-axial accelerometer embedded in a Huawei GR5 with an Android operation system. The results are given in two forms such as estimated IRI (eIRI) and calculated IRI (cIRI) and both are an estimate of the value of the IRI defined by the ASTM E1926-98 standard (ASTM 2003). eIRI value is derived based on peak and root mean

Table 3. Summary of road inventories in the rural road network.

Road type	Number of roads (N)	Average width (m)	Total length (km)
Single-lane roads	59	3.2	192.35
Two-lane roads	36	5.6	241.65
Total	95	-	434.00

Table 4. Summary of traffic characteristic in the rural road network.

Traffic volume (ADT)	Mean (μ)	844 vehicles/day
Percentage of roads	<500 veh/day	39%
	500–1000 veh/day	31%
	1000–1500 veh/day	13%
	>1500 veh/day	17%
Vehicle composition	Motorcycle	68%
	Three-wheelers	20%
	Good vehicles	5%
	Buses	1%

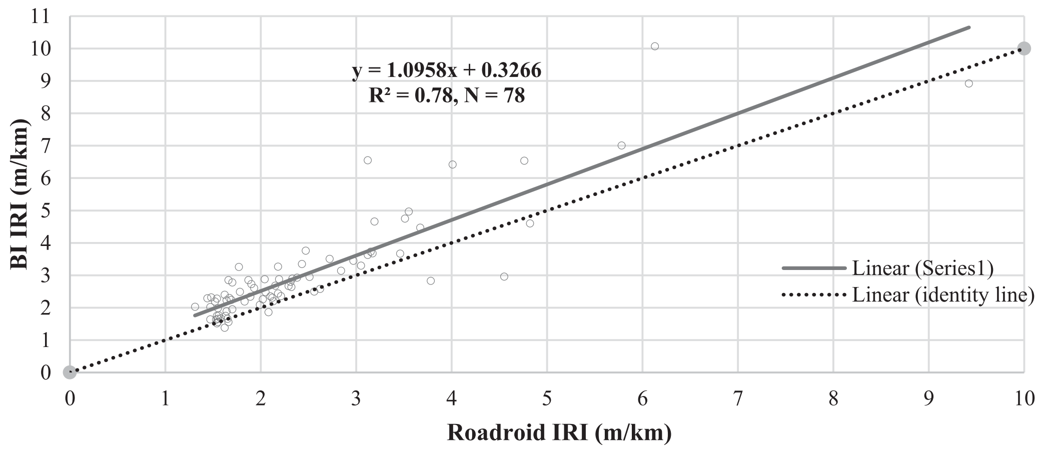

Figure 1. Comparison between IRI measurement using bump integrator and Roadroid mobile application.

square (RMS) vibration analysis at a speed range of 20–100 km/hr and cIRI is derived on quarter car simulation at the speed range of 60–80 km/hr (Gamage *et al.* 2016). In the data collection, Roadroid App is tuned for lower survey speeds down to 30 km/h. In the study, the roughness survey is conducted in a speed range of 30–40 km/hr, therefore eIRI values were selected as the output.

Figure 1 shows the relationship between IRI from bump integrator and eIRI from the Roadroid app for the road network. It is observed that Roadroid slightly underestimates the IRI measurements compared to the bump Integrator IRI. However, the applicability of eIRI with bump integrator IRI was confirmed by a regression model given in Equation (9), with an adjusted coefficient of determination (R^2) of 0.77 and *p*-value of 0.001 under 5% significance level.

$$IRI_{BI} = 1.0958 IRI_{Roadroid} + 0.3266 \tag{9}$$

Where IRI_{BI} is the roughness value measured by bump integrator in-unit m/km; $IRI_{Roadroid}$ is the eIRI value measured by 'Roadroid' app in-unit m/km

Relationship between IRI and pavement distress condition

Six key distresses that are prevalent in low volume roads have been identified during the field investigation, namely, pothole (POT), ravelling (RAV), cracking (CRA), patches (PAT), edge gap (EDG) and edge break (EDB). The summary of identified distresses from the selected road network is shown in Table 5. Edge gap length is calculated by measuring linear length along both sides of a pavement section which exceeds the gap between carriageway and shoulder more than 10 cm. The other distresses are recorded in terms of the percentage surface area affected by the distress. For the distress types similar to cracking, the boundary area surrounding the crack is measured to define the affected area. All the measurements are taken by the walking survey. A sample of roads from the low volume road network with different distress levels is shown in Figure 2.

Table 5. Summary of identified distresses in the rural road network.

Distress type	Number of roads with distress (N)	Maximum observed density (percentage of the total surface area)
Ravelling (RAV)	32	57.01
Pothole (POT)	17	0.44
Edge breaking (EDB)	43	12
Edge gap (EDG)	15	13.81
Cracking (CRA)	35	16.6
Patching (PAT)	25	5

The observed IRI measured by bump integrator for all 95 road segments is in the range of 1.38 m/km to 13.5 m/km. Furthermore, most of the distress progression were identified to take place beyond IRI of 3 m/km. Ravelling is the most common distress type observed, in the new pavement, as well as older ones with IRI, is range from 3 m/km to 13 m/km. In addition to that, road sections with pothole are likely to be older pavements with IRI greater than 6 m/km. The road segments which shown edge breaks are likely to represent roads with good IRI, but failure between carriageway and shoulder due to weathering effect and drainage problems.

The Pearson correlation analysis was conducted to find the relationship between IRI and each distress type separately. Three types of regression functions were tested; linear, quadratic non-linear and logarithm non-linear and the best representative function is selected by statistical analysis. The test values of the coefficient of determination (R^2), hypothesis and analysis of variance (ANOVA) were used to select the best-fitted function. The best-fitted functions are shown in Figure 3, and the statistical relationships for each distress type were illustrated in Table 6.

Based on the distress type and roughness data analysis, there is a good correlation between all distress types except patching. The regression models are developed between roughness and distress type except patching shown that, low significance (p-value < 0.05) in estimating the roughness values. This also depicts, the likely periods of the pavement overall life these distress tend to emerge. For example for potholes, the constant of the regression model is 12.6, whereas for ravelling or edge-breaking it is 5.4 and 2.15 respectively. This suggests, potholes generally occur in older pavements whereas, ravelling and edge breaks were initiates in relatively new pavements.

Figure 2. Example of road sections with different distress levels in rural road network.

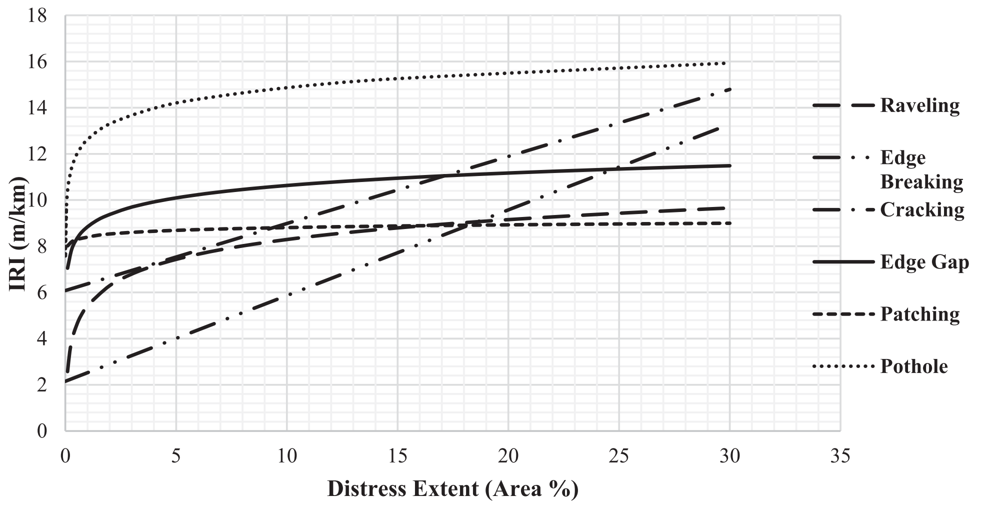

Figure 3. IRI vs distress density functions.

Further, multiple linear regression analysis is conducted to develop basic models to interpret the combined effect of distresses on roughness concerning different stages of pavement life.

Model 1: IRI vs all distresses

A multiple regression model developed to assess the relationship between IRI and distresses for all stages of pavement life. All the distresses identified in this study used for this model which is shown in Equation (10).

$$IRI = 2.90 + 0.155RAV + 0.292CRA + 0.401EDG \quad (10)$$

Where RAV and CRA are the ravelling and cracking area as a percentage respectively; EDG is the percentage of the edge gap more than 10 cm in linear length along both side of the pavement

Ravelling, cracking and edge gap are shown significant evidence that those distresses represent IRI accurately. However, edge break, pothole and patching are excluded due to lower significance (p-value > 0.05). Even though the correlation is high in this model, the dependency of IRI on some distresses are relatively low when considering the distresses for pavements of any age range. To evaluate the accuracy of roughness as a condition evaluation method, the analysis is continued by separating pavement sections based on the pavement age.

Sub model 1: for the early stage of a pavement

The first model was to fit the relationship between IRI to distress in the initial stage (within 5 years of construction) of the pavement. The distresses identified in new pavements are ravelling, edge gap and patching and the linear model is shown in Equation (11).

$$IRI = 2.538 + 0.095RAV + 1.545EDG + 1.158PAT \quad (11)$$

Where PAT is the patching area as a percentage

Sub model 2: for older pavements after pothole progression

The second sub-model is developed to find the relationship in the older pavement after pothole propagation. The basic form of multiple regression equation is defined as in Equation (12).

$$IRI = 6.135 + 0.107RAV + 11.353POT + 0.25CRA \quad (12)$$

Where POT is the pothole area as a percentage

The results have shown that the presence of ravelling and pothole can be captured by IRI on older pavements accurately. Even though pothole is excluded in Model-1, it is observed that when an older pavement is taken into consideration, the impact of the pothole is highly significant. The edge gap is the important distress identified in this study, since most researchers, pay less attention to edge gap related factors. Especially in rural roads, due to the limited width of the carriageway edge gap

Table 6. Summary of IRI vs distress density functions.

Distress type	Correlation (R)	Best fitted function	*P*-value
Ravelling (RAV)	0.61	IRI=5.4315 + 1.2421 ln (RAV)	0.001
Pothole (POT)	0.55	IRI=12.622 + 0.9732 ln (POT)	0.021
Edge breaking (EDB)	0.55	IRI=2.1501 + 0.3711 (EDB)	0.001
Edge gap (EDG)	0.52	IRI=8.8401 + 0.7774 ln (EDG)	0.049
Cracking (CRA)	0.34	IRI=6.0786 + 0.2904 (CRA)	0.048
Patching (PAT)	0.11	IRI=8.4096 + 0.172 ln (PAT)	0.616

has more influence on roughness progression on roads. Moreover, the roads with higher edge gap are potentially risk introduced to motorcycle and three-wheeler users. Since in these roads 88% of traffic is consisting of motorcycles and three-wheelers, the edge gap is far more important to the users from the perspective of safety performance.

Based on the output from the collinearity test, the obtained variance inflation factor (VIF) for all distresses are less than 10. Therefore, it can be concluded there is no multicollinearity symptom in any model. Moreover, the statistical summary of the developed three models is shown in Table 7.

Relationship between IRI vs PCI

The detail description of distress data was converted into a PCI index in accordance with the ASTM D 6433–07 (ASTM 2007). When calculating the PCI, deduct value for high severity condition is considered and based on the density, the PCI calculation process is continued.

It was found that calculated PCI has a strong relationship with IRI for the selected road network as shown in Figure 4. The relationship is developed with a range of IRI is 1.38 m/km to 13.5 m/km and the calculated PCI value varies from 9 to 100. The non-linear regression model using the sigmoidal function has represented the best-fitted function with an adjusted coefficient of determination (R^2) 0.75 for IRI with PCI and shown in Equation (13).

$$IRI = \frac{10.98}{1 + \left(\frac{PCI}{65.9}\right)^{4.27}} \tag{13}$$

Table 7. Summary of developed models.

Regression functions			
Model −1: IRI = 2.90 + 0.155 RAV + 0.292 CRA + 0.401 EDG			
Sub model −1: IRI = 2.538 + 0.095 RAV + 1.545 EDG + 1.158 PAT			
Sub model −2: IRI = 6.135 + 0.107 RAV + 11.353 POT + 0.25 CRA			
Distress types (Model-1)		*P*-value	Variance inflation factor (VIF)
Ravelling		0.000	1.213
Edge gap		0.000	1.184
Cracking		0.000	1.124
Distress types (Sub model-1)		*P*-value	Variance inflation factor (VIF)
Ravelling		0.000	1.532
Edge gap		0.000	1.159
Patching		0.001	1.423
Distress types (Sub model-2)		*P*-value	Variance inflation factor (VIF)
Ravelling		0.001	1.213
Pothole		0.033	1.201
Cracking		0.049	1.122
Accuracy of models			
Statistical parameter	Model-1	Sub model - 1	Sub model – 2
R^2	0.72	0.52	0.79
Adjusted R^2	0.71	0.50	0.71
Standard error	1.81	0.98	1.18
Degrees of freedom (df)	95	72	17

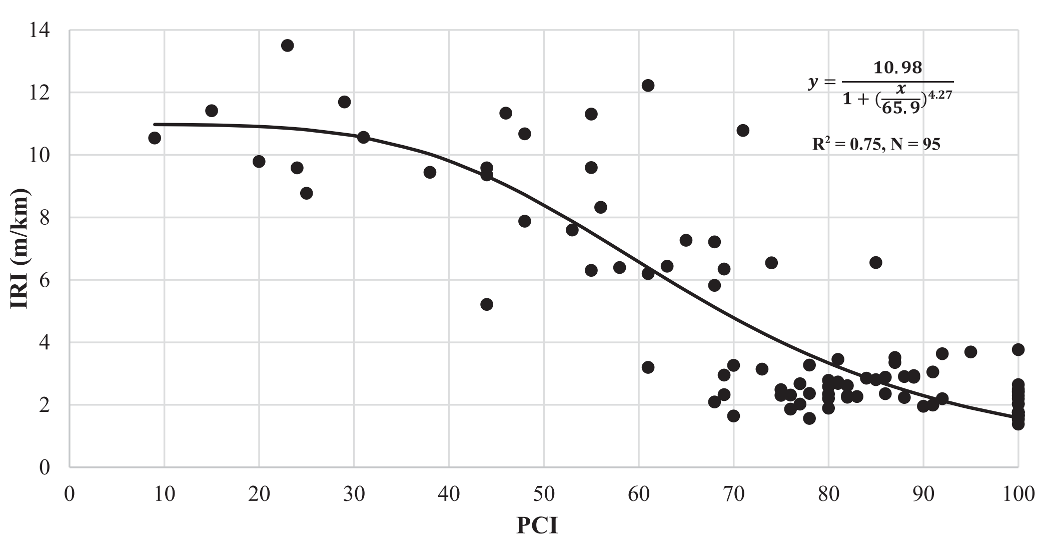

Figure 4. Relationship between IRI and PCI.

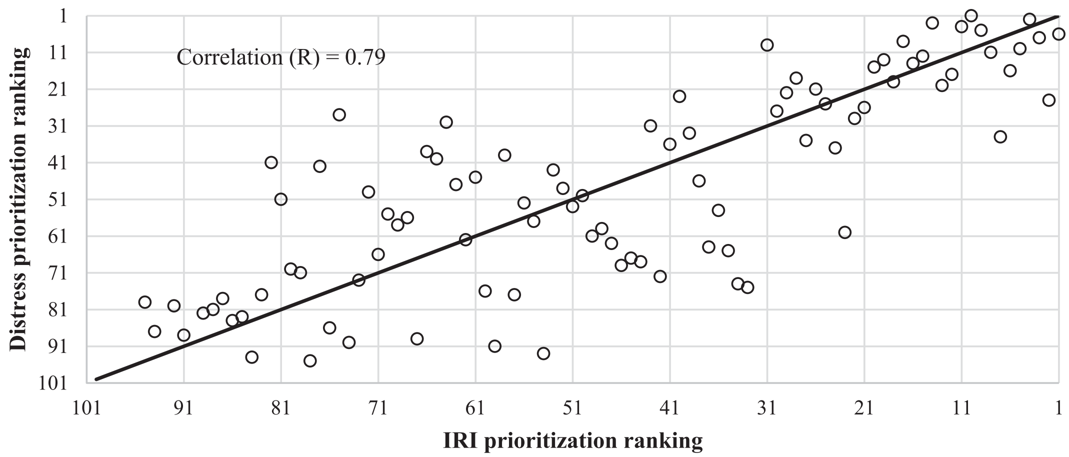

Figure 5. Comparison between IRI and distress prioritization ranking.

Categorisation of roads based on IRI and PCI

The applicability of IRI for pavement condition measurement is evaluated by prioritisation of the selected 95 road sections in terms of IRI and PCI respectively. The worst first method is used in the prioritisation. The road segments with the highest IRI considered as rank 1 based on roughness while the segment with the least PCI value considered as rank 1 in terms of distress. It appears in Figure 5, that ranking in the mid-range is not well correlated whereas good and poor ranges (two extremes) are well correlated. Overall, the results have shown that a strong relationship with a correlation coefficient of 0.79, which provides sufficient evidence of the accuracy of IRI as a condition measurement parameter.

Furthermore, categorisation is conducted for selected road sections based on defined IRI and PCI ranges. The categories are defined by a panel of experienced highway engineers in local agencies in Sri Lanka. Moreover, IRI descriptive categories defined by Feighan *et al.*, 2015 are similar to the categories defined for this study. That categorisation is done as very poor (IRI > 7 m/km), poor (5 m/km < IRI < 7 m/km), fair (4 m/km < IRI < 5 m/km), good (4 m/km < IRI < 3 m/km) and very good (IRI < 3 m/km) for roads with annual average daily traffic (AADT) less than 2000 veh/day.

In the comparison, the road sections in the PCI range are matched with the appropriate IRI range with IRI tolerance of ±0.5 m/km. A similarity index as a percentage is developed based on the categorisation shown in Table 8. Out of 95 road sections selected from the network, 79 road sections shown similarity in both condition measurement methods. The road segments in the middle range shown the least similarity (58%) while upper and lower ranges are shown a relatively higher similarity index. These results provide strong evidence about the suitability of IRI as a condition measurement parameter for the low volume road network level prioritisation process.

Table 8. Categorisation of pavements in terms of IRI and PCI.

Category of condition	IRI range (m/km)	PCI range	
Good	<3	80–100	
Fair	3–7	55–80	
Poor	>7	<55	
Similarity index			
Category	Number of roads in PCI range	Number of roads in IRI range	Similarity index
Good	49	44	90%
Fair	26	15	58%
Poor	20	20	100%

Conclusion

Smartphone-based roughness measurement is used to find a cost-effective solution to collect roughness data considering the funding constraints of local road agencies. Instead of using precise roughness measuring equipment still, smartphone-based applications provide an accurate measurement. In this study, it is observed that Roadroid is underestimated actual IRI value slightly but within the acceptable tolerance limit, therefore the smartphone-based roughness collection method is a viable cost-effective solution for local agencies to collect network-level roughness data.

The influence of distress types on pavement roughness and the ability of IRI to capture the presence of distress on the pavement surface is also investigated in this study. It is observed that higher correlation (R) with IRI for ravelling (0.61), pothole (0.55), edge breaks (0.55) and edge gap (0.52). The other key finding of the study is the impact of the edge gap on pavement roughness on rural roads with limited carriageway width. Three models developed by introducing combine effects of distresses on IRI by multivariable regression analysis and it provided sound relationships for pavement different age categories. Moreover, the relationships show statistical significance for observed distress such as ravelling, edge gap and cracking. Especially, the presence of ravelling is captured by IRI in both new and older pavements more accurately than others. Pothole has a relatively weaker relationship when combine distresses are considered for new pavements, but when analyzing older pavement separately, it has shown the highest impact on roughness. From that, pothole can be considered as predominant distress type in an older pavement along with ravelling and cracking. Moreover, based on the PCI and roughness values derived for the road network a regression model was developed between the PCI and IRI. The regression model further validates that the roughness value of the pavement provides a satisfactory assessment of the overall pavement condition.

From the categorisation of roads based on their overall condition using both IRI and PCI values indicates that there is a similarity of 83% in the assessment based on two indices. This further validates that consistent maintenance planning decisions will be made using roughness value-based evaluation of the pavements which would be comparable to those made using distress condition data based evaluation methods. This is also useful to establish threshold values for corrective and preventive maintenance strategies at the network level. Based on the results, it can be established that a similar assessment would be made on the pavement condition by evaluating either distress data or roughness data. Therefore, roughness information can be obtained at a lower cost and in less time would provide a reliable metric to evaluate the road condition especially for network-level condition evaluation in rural roads.

It can be concluded that pavement roughness values accurately represent the distress conditions prevalent on rural road pavements and decision making done based on the roughness results are consistent to that made with distress condition data. Compared to the cost and time required to collect distress condition data at network level, this would create significant savings to the local agencies. Furthermore, the collection of roughness data is also simplified with the use of smartphone-based apps. The results of which is validated by comparing with the results from conventional roughness measurement methods. Therefore, it can be concluded that the smartphone-based roughness data collection method is a viable approach for rural road network-level condition evaluation. The findings of the study would promote the use of objective quantitative approaches to evaluate pavement condition in rural roads by the local agencies which would enable them to adopt pavement maintenance management systems for their maintenance planning and ensure the roads are maintained more efficiently.

Acknowledgment

The research was funded by the Senate Research Committee (Grant No SRC/LT/18/19) of the University of Moratuwa, Sri Lanka. Data collection was carried out with the support given by the Mr. R.M. Amarasekara and Integrated Road Investment Program (iRoad), Road Development Authority, Sri Lanka.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Senate Research Committee of the University of Moratuwa, Senate Research Grant Sri Lanka under Grant No SRC/LT/18/19.

ORCID

R. M. K. Sandamal http://orcid.org/0000-0002-7451-4667

Data availability

The data that support the findings of this study are available from the corresponding author, [R. M. K. Sandamal] upon reasonable request.

References

Abiola, O.S., Kupolati, W.K., and Odunfa, S.O., 2014. Predicting visual pavement score from international roughness index. *In: International Conference on Biological, Civil and Environmental Engineering*, 17–18 March 2014 Dubai.

Aleadelat, W., *et al.*, 2018. Evaluation of pavement roughness using an android-based smartphone. *Journal of Transportation Engineering, Part B: Pavements*, 144, 3.

Asian Development Bank, 2018. *Compendium of best practices in road asset management*. Philippine: 1550 Metro Manila.

ASTM International, 2003. ASTM E1926-98. Standard practice for computing international roughness index of roads from longitudinal profile measurement.

ASTM International, 2007. ASTM D6433-07. Standard practice for roads and parking lots pavement condition index surveys.

Avinash, A.N., *et al.*, 2014. Performance evaluation of low volume flexible pavements-a case study. *In: 2nd Transportation and development conference*, 2 June 2014 India. ASCE, 2014.

Beckemeyer, C.A., 1995. *Rural road condition survey guide*. Canada: SD Department of Transportation Office of Research.

Bisconsini, D.R., *et al.*, 2018. Pavement roughness evaluation with smartphones. *International Journal of Science and Engineering Investigations*, 7, 43–52.

Buttlar, W. G., Alavi, A., and Brown, H., 2018. *Pavement roughness measurement using android smartphones: case study of Missouri roads and airports*. Columbia: Department of Civil and Environmental Engineering University of Missouri.

Buttlar, W. and Islam, S., 2014. *Integration of smart-phone-based pavement roughness data collection tool with asset management system*. Washingto D.C: USDOT University Transportation Center.

Cantisani, G. and Loprencipe, G., 2010. Road roughness and Whole Body vibration: evaluation Tools and comfort Limits. *Journal of Transportation Engineering*, 136 (9), 818–826.

Douangphachanh, V. and Oneyama, H., 2013. A study on use of smartphones for road roughness condition estimation. *Journal of the Eastern Asia Society for Transportation Study*, 10, 1551–1564.

Eriksson, J., *et al.*, 2008. The pothole patrol: using a mobile sensor network for road surface monitoring. *In: 6th International Conference on Mobile Systems, Applications, and services*,17–20 June 2008, Breckenridge, Colorado, USA.

Feighan, K., *et al.*, 2015. Recent developments in pavement management on Irish national roads. *In: 9th International Conference on Managing Pavement Assets*, 18–21 May 2015 Washington, D.C.

Gamage, D., Pasindu, H.R., and Bandara, S.J., 2016. Pavement roughness evaluation method for low volume roads. *In: 8th International conference on maintenance and rehabilitation of pavements*, 5–7 December 2016 Singapore, 976–985.

Gunasoma, H.D.S. and Pasindu, H.R., 2016. Model development for optimization and prioritization of pavement maintenance for provincial road networks. *In: 10th Asia Pacific Conference on Transportation and the Environment*, 8–10 November Malaysia.

Hass, R., Hudson, W.R., and Zaniewski, J.P., 1994. *Modern pavement management*. Florida: Krieger Publishing Company.

Islam, S., *et al.*, 2014. Measurement of pavement roughness using android-based smartphone application. *Transportation Research Record: Journal of the Transportation Research Board*, 2457, 30–38.

Kirbas, U., 2018. IRI sensitivity to the influence of surface distress on flexible pavements. *Coating Research Board*, 8 (271), 10.3390.

Lin, J.D., Yau, J.T., and Hsiao, L.H., 2003. Correlation analysis between international roughness index (IRI) and pavement distress by neural network. *In: 82th Annual Meeting of the Transportation Research Board*, January 2003 Washington, D.C.

Mane, A.S., *et al.*, 2016. Methodology for pavement condition assessment and maintenance of rural road. *In: National conference on fifteen years of PMGSY*, 6–7 August 2016 Roorkee, India. C-6, 1–14.

Mathew, B.S. and Isaac, K.P., 2014. Optimization of maintenance strategy for rural road network using genetic algorithm. *International Journal of Pavement Engineering*, 15, 352–360.

Moazami, D., *et al.*, 2011. The use of analytical hierarchy process in priority rating of pavement maintenance. *Scientific Research and Essays*, 6, 2447–2456.

Morosiuk, G. and Michael, R., 2004. *Modeling road deterioration and work effect in HDM-4*. Manila, Philippines : Asian Development Bank.

Mubaraki, M., 2016. Highway subsurface assessment using pavement surface distress and roughness data. *International Journal of Pavement Research and Technology*, 9, 393–402.

Muthuma, P., Mubea, K., and Mundia, C.N., 2016. Assessment of impacts of road infrastructure using GIS and remote sensing: A case study of yatta sub country. *International Journal of Science and Research*, 5, 1210–1219.

Nkomo, S.L., Desai, S., and Peerbhay, K., 2016. Assessing the conditions of rural road networks in South Africa using visual observations and field-based manual measurements: A case study of four rural communities in KwaZulu-Natal Province. *Review of Social Sciences*, 1, 42–55.

Pantuso, A., *et al.*, 2019. Analysis of pavement condition survey data for effective implementation of a network level pavement management program for Kazakhstan. *Sustainability*, 11 (901), 10.3390.

Park, K., Thomas, N.E., and Lee, K.W., 2007. Applicability of the international roughness index as a predictor of asphalt pavement condition. *Transportation Research Record: Journal of Transportation Engineering*, 133, 706–709.

Pogson, C., 2013. *Condition assessment of District roads*. US: USDOT Region V Regional University Transportation Center.

Prasad, J.R., *et al.*, 2013. Development of relationship between roughness (IRI) and visible surface distresses-a study on PMGSY roads. *Procedia - Social and Behavioral Science*, 104, 322–331.

Roadroid Smartphone Apps, Roadroid Pro2. Available from: http://www.roadroid.com/home/app. [Accessed July 23, 2019].

Shah, Y.U., *et al.*, 2013. Development of overall pavement condition index for urban road network. *Procedia - Social and Behavioral Science*, 104, 332–341.

Tai, Y., Chan, C., and Hsu, J.Y., 1998. Automatic road anomly detection using smart mobile device. *In: 15th Conference on Artifical Intelligence and Applications*, 18–20 November 2010 Hsinchu, Taiwan.

Tawalare, A., and Raju, K.V., 2016. Pavement performance index for Indian low volume roads. *Perspective in Science*, 8, 447–451.

Thube, D.T., Jain, S.S., and Parida, M., 2007. HDM-4 based optimal maintenance strategies for low volume roads in India. *Road and Transport Research*, 16 (4), 3–15.

Yeganeh, S.F., *et al.*, 2017. Validation of smartphone-based pavement roughness measures. *AUT Journal of Civil Engineering*, 1, 135–144.

Zhang, M. and Gao, S., 2017. Evaluation of rural road asphalt pavement performance based on matter element analysis. *In: 2nd International Conference on Civil Engineering and Rock Engineering*, 27 June 2017 Guangzhou, China.