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An Objective Method for Gravel Roads Riding Quality Utilizing Smartphones Data Collection and Artificial Neural Network Modelling

Osama Abu Daoud*, Khaled Ksaibati, Manar Farraj

Department of Civil and Architectural Engineering, University of Wyoming, Laramie, US
Email: *oabudaou@uwyo.edu, khaled@uwyo.edu, manar.farraj@yahoo.com

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Abstract

The current limitation in maintenance budget and resources necessitates developing new cost-effective techniques for gravel roads management systems (GRMS). Thus, the Wyoming Technology Transfer Center (WYT2) has started developing a holistic automated GRMS. Utilizing smartphones in gravel roads data collection is one of the main features in the proposed system. In this study, smartphones were used to collect gravel roads condition data in terms of International Roughness Index (IRI) and corrugation to develop an objective computational method to estimate the riding quality on gravel roads. The developed method will help local agencies to reduce subjectivity in their data collection process and support them with a solid computational justification for their evaluation data and decisions. Two analyses have been carried out to achieve the purpose of this study. Artificial Neural Network ANN method and linear regression were used to develop the riding quality model. The linear regression resulted in a model that has a 0.8242 coefficient of determination (R^2) value which means that the developed riding quality model can represent 82.42% of the collected data. The achieved R^2 value is considered sufficient for GRMS purposes. In addition, the developed ANN model has a prediction accuracy of 92.5%. The achieved prediction accuracy shows that the ANN model can predict the riding quality significantly better than the linear regression, with 12.5% higher accuracy. Furthermore, thresholds for the gravel roads IRI were suggested and introduced in this study to be the first IRI thresholds for gravel roads in the literature. Based on the suggested threshold, the gravel roads IRI has three classes: smooth, acceptable and rough. The gravel road segment can be classified in terms of IRI to be smooth, acceptable, or rough if its IRI value is less than 284, between 284 and 496, or more than 496 inch/mile, respectively.

Keywords

Gravel Roads, Smartphones, Riding Quality, IRI Thresholds, Corrugation, Roads Management

1. Introduction

Road surfaces can be classified into two categories based on their surface nature: paved and unpaved (gravel) roads. Gravel roads are unimproved roads with surfaces constructed from natural soil and stones [1]. Federal Highway Administration (FWHA) records show that the United States owns and maintains approximately 1,370,000 miles of unpaved roads, which form 35% of the total roads network length. The records show that the total mileage of gravel roads in the United States decreased in the last few decades. **Figure 1** shows historical changes in gravel roads total length in the U.S. [1].

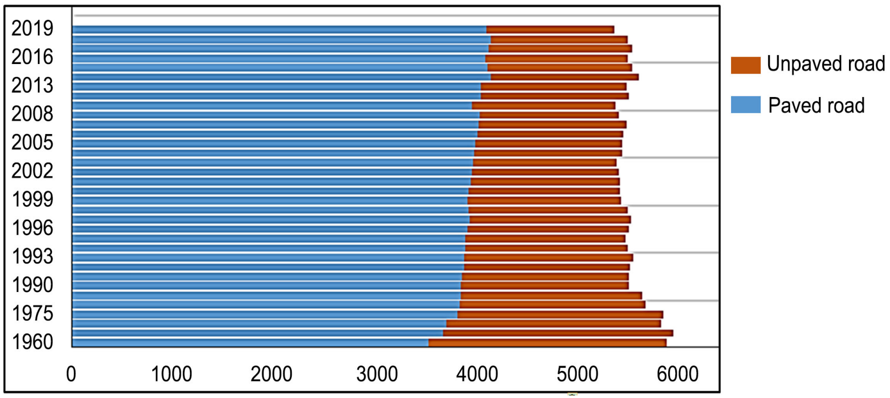


Figure 1. Historical changes in gravel roads total length in the U.S. in miles.

Gravel roads form about 90% of the local roads network in the state of Wyoming. This percentage of gravel roads is considered significantly high. These gravel roads serve various land use purposes. Gravel roads in Wyoming are located in residential, agricultural, and industrial areas. This variety in land use results in considerable differences in traffic loads. Heavy traffic loads lead to higher deterioration rates and reduce the service life of gravel roads. Therefore, developing an advanced and integrated Gravel Roads Management System (GRMS) has become a necessary need. Gravel roads, like most local roads, are usually managed by local agencies. Most of the time, the local agencies have good experience in maintenance procedures, but not in roads management. Because of that, any work in developing a GRMS should consider local agencies' needs.

Wyoming Technology Transfer Center (WYT2/LTAP) has recently started a process to develop a new gravel roads management system (GRMS). This new in-progress GRMS aims to help local agencies in managing their gravel roads in a simple and cost-effective way [2]. Data collection and building the database are the most challenging parts when developing gravel road management systems [3]. Therefore, the WYT2/LTAP is in process of introducing a holistic gravel roads data collection approach using smartphone applications and sensors [2]. However, one of the most used terms in gravel roads condition assessment is the Riding Quality Rating Guide (RQRG). Using a single term to demonstrate the overall gravel road condition reduces the data collection cost and time, and it helps in managing roads with limited resources [3]. RQRG is a subjective method to evaluate the gravel roads condition by determining the riding quality level. Many agencies have developed their own riding quality manuals to guide their inspector in evaluating the gravel roads. Since RQRG is a subjective method, the results still depend on the inspector's personal judgment.

In this study, an objective method to determine the RQRG is introduced. The RQRG is similar to the Present Serviceability Rating (PSR) on paved roads since in both rating systems the evaluation is based on road users' judgment and comfort. Thus, two factors are expected to have the strongest effect on riding quality: road roughness and surface corrugation. Modern smartphones' accelerometers and cameras were utilized in collecting gravel road roughness and corrugation data for the purpose of this study. The data in this study were collected using an Android mobile application called "Roadroid". This android application collects the roughness data by utilizing the mobile built-in accelerometer, while the corrugation data is collected by capturing photos using the mobile camera and classifying them using a sophisticated image classifier on the "Roadroid" cloud. The introduced method aims to provide pavement inspectors and evaluators with a unique method to determine riding quality. Utilizing such a method will eliminate biases due to the evaluator's judgment on the riding quality rating, resulting in the riding quality data being more consistent when used for planning and prioritization of gravel roads maintenance. In addition, local agencies will have a solid justification for their riding quality data.

2. Background

Gravel roads condition evaluation methods are mainly categorized into two groups: objective evaluation for each distress, and subjective evaluation for the riding quality. Many agencies developed their own techniques to evaluate gravel roads conditions by assessing existing distresses individually [4]. One of the earliest manuals is the U.S. Army Corps of Engineers assessment system (USACE). The USACE procedure has an index called Unsurfaced Road Condition Index (URCI). This index value depends on the existing distress severity level and area. The distress severity level and area is used to calculate a deduct value. After that, all the calculated deduct values are used in calculating an overall URCI for the gravel road segment [4]-[6].

There are more recent studies involving systems for evaluating gravel road quality. In 2012, Bhoraskar *et al.* carried out a study to introduce a Gravel Road Condition Index (UPCI) based on existing surface distresses [7]. In addition, the

World Bank has developed several procedures to evaluate gravel road conditions such as the Roads Economics Decision Model and the Deterioration of Unpaved Roads Model (DETOUR) [8]. The DETOUR model predicts the gravel road segment condition based on the environmental condition, road geometry and the gravel road structural characteristics [1] [8]. In another study, the University of New Hampshire and FHWA developed the Road Surface Management System (RSMS). RSMS evaluates gravel roads based on the existing distresses. The main feature of the RSMS is that the inspector evaluates the gravel road segment directly without assigning a score for each distress [9]. CSIR Transportek has also developed a Standard Visual Assessment Manual (SVAM) for unpaved roads. The SVAM has three categories for roads data. The first category is the basic data for road management and includes data about the existing distresses and their severity. The second category provides information about the extent of the existing distresses. The distresses extension is estimated by calculating the ratio between the distress area and the total road segment area. The third category is the advanced level data which includes the layers' thicknesses, material characteristics of the gravel layer, and geometric features of the road [10]. Another rating system called the Subjective Rating System (SRS) has been developed by Central Federal Lands Highway Division. This Subjective Rating System evaluates gravel road conditions by considering five distresses and assigning a condition rate for each segment. The condition rating is based on a scale from 0 to 10, where 10 is the best condition and 0 is the worst [11]. However, most manuals evaluate gravel road distresses individually and very few provide an overall rating for road segments and mostly those manuals are complicated and require a massive number of resources. This complicity in the available methods and manuals make it difficult for local agencies for adapt and use them. Gravel roads are usually managed by local agencies with limited resource and fund. In addition, location agencies are good in maintenance work than management and evaluation. Usually, the overall assessment for gravel roads is a subjective rating determined by evaluating the riding quality.

Riding quality is a very popular indicator for gravel road conditions since most pavement distortion and distresses, including cracking, unevenness, corrugation, potholes, and rutting, affect the riding quality directly. However, this study considered only the gravel roads roughness and corrugation in order to predict and estimate the riding quality. This decision was made based on the previous experience with gravel roads. Generally, the most common distortion in gravel roads are the corrugation. In addition, the roughness is considered since it is the most distortion related to riding quality. The formation of distresses on gravel roads over time increase the road segment roughness, which leads to reduced driving quality. As a result, the road service life is decreased [12]. Road roughness and riding quality have a direct impact on vehicle operating costs (VOCs) since the rough surface of the road generates vibrations that transfer through the suspension and tires to the vehicle body [13]. The generated vibrations cause damage to vehicle parts and significantly increase overall fuel consumption [13] [14]. Recently, many road management agencies have developed their own gravel roads visual assessment manuals, such as the manual developed by the South African Council for Scientific and Industrial Research (CSIR) and the PASER manual, which was developed the by Wisconsin Department of Transportation. Even though the PASER rating system is the most used method in evaluating gravel roads in the U.S., its short scale negatively affects the road inspector's judgment. Usually, collecting evaluation data utilizing a short scale results in two types of errors: errors of leniency, and central tendency [1]. Therefore, the WYT2/LTAP modified and expanded the PASER system to a new rating system called Riding Quality Rating Guide (RQRG) that uses a scale range from 1 to 10. The rating range expansion aims to enhance evaluation data by increasing the predicted accuracy and liming the error sources. In addition, the RQRG demonstrates the road user's satisfaction in terms of their riding comfort over a gravel road segment [15] [16]. As a result, the RQRG is highly affected by road surface distortions such as corrugation, unevenness and potholes. In the RQRG rating system 10 represents the best condition and 1 represents the worst. **Table 1** shows the Riding Quality Rating Guide summary [15] [17].

Table 1. Riding quality rating guide summary [16].

Rating		Description
10	Excellent	Riding quality similar to riding on a good paved road.
9	Very Good	Riding quality similar to a worn paved road.
8	Good	Minor roughness and unevenness.
7	Good	Significant roughness and unevenness.
6	Fair	Several types of surface distresses and significant roughness.
5	Fair	Severe roughness leading the driver to significantly reduce vehicle speed.
4	Poor	Very severe roughness and possibility for vehicle damage.
3	Poor	High possibility for vehicle damage. Difficulties in controlling the vehicle.
2	Very Poor	Difficulties in controlling the vehicle. Passenger vehicles at high risk of damaged undercarriage parts.
1	Failed	Difficulties in controlling the vehicle. Passenger vehicles at high risk of losing the ability to move.

Evaluating gravel road roughness and determining the effects of road irregularities on vehicles can be carried out using several procedures [18]. In such procedures, the surface roughness defined as a kind of pavement distortion occurs in a perpendicular direction to the pavement surface plane. Roughness could be determined by several methods such as International Roughness Index (IRI) or Unevenness Index (UI). Most of the modern procedures evaluate roughness in terms of International Roughness Index (IRI) [19]. In the last few decades, many research institutes have worked to develop advanced equipment to measure IRI. Cybernetics Corporation developed a tool called the Longitudinal Profiling System to measure road roughness by utilizing an infrared laser and accelerometer. The Longitudinal Profiling System measures the roughness in terms of IRI under the wheel path [20]. Another tool called Opti-Grade was developed to collect gravel road roughness data by the Forest Engineering Research Institute of Canada (FERIC). The Opti-Grade includes three components; an accelerometer, a GPS, and a data processing system. Opti-Grade has been tested on a small network, and its capability to collect data from large gravel road networks such as county road has not been verified yet [21]. Zhang and Elaksher introduced another approach to utilize unmanned aerial vehicles (UAV) in recognizing surface defects. This method is able to identify the density and severity of surface defects by analyzing a three dimensional model of the gravel road surface using image algorithms [19] [22]. In another study conducted by Alhasan *et al.*, gravel roads roughness was calculated using a laser scanner. Such laser scanners are typically employed to generate three dimensional maps for the road surface. Afterward, statistical analysis was utilized to predict the IRI [23] [24].

Despite of these advances, there is still a lack in developing an objective method to determine the riding quality on gravel roads. Most of the available objective methods are impractical and can be helpful only in research [25]. In addition, the available objective methods require a significant amount of resources, which lead them to be too expensive. Moreover, the measurements of these methods have a certain level of subjectivity, especially in collecting distresses data. Therefore, many agencies still prefer to use visual inspections [26]. Thus, utilizing smartphones features and capabilities attracted researchers in the gravel roads field. Employing smartphones in the gravel roads data collection process is a very promising practical and cost-effective method.

Utilization of smartphones in gravel roads data collection is still limited. Most of the previous research was carried out on paved roads. The dynamic nature of gravel roads make them considerably different from paved roads. However, smartphone accelerometers can be used to detect vehicle vibrations caused by road roughness [27] [28]. Another smartphone feature is the ability to use the built-in GPS to automatically referencing the evaluated segments [29] [30]. In 2017, Harikrishnan and Gopi utilized the threshold technique with the Gaussian model to recognize and evaluate pavement potholes and bumps. Vehicle vibrations were measured using a smartphone's built-in accelerometer. Then, an advanced filter was used to minimize the abnormal data points. The overall accuracy of this model reached 90% [31]. In another study, a modern mobile application called "Smart-Patrolling" was developed to collect road surface data in terms of potholes and bumps. The smartphone was fixed in different locations inside the vehicle to study the effect of the smartphone's placement on the collected data. The application showed an accuracy level of 89% [32]. Another mobile application, "Road Data Collector," was developed in 2017 by Allouch *et al.* in order to employ machine learning concepts in road data collection. The built-in mobile accelerometer and gyroscope were used for the pothole data collection process. Several machine learning methods were applied in this study such as Decision Tree and Naïve Bayes [33]. More recently, a crown sensing-based system was built to be utilized in road surface data collection using smartphones. The mobile accelerometer and GPS were utilized to collect spatial data of the road surface. The results of this study showed that the crown sensed data can be efficient in road surface evaluation [34].

In conclusion, current efforts to automate the data collection of gravel roads is still impractical and needs more development to be a convenient resource for gravel road agencies. In addition, there is a need to have an objective method to determine the riding quality of gravel roads. Therefore, this study is introducing a new computational method to determine the riding quality of gravel roads in consideration of the capabilities and resources of local agencies. The proposed method is a cost-effective approach and can deal with the dynamic nature of gravel road conditions.

3. Methodology

In this study, an Android application called "Roadroid" was utilized to collect gravel road data. The application collected IRI and corrugation data. In addition, the gravel road rating system (GRRS) was used to determine the riding quality for the tested gravel road segments. Later on, the collected data was statistically analyzed to develop a computational formula for the riding quality. Afterward, IRI classification limits were introduced. Four hundred and twenty-eight gravel road segments were evaluated in Laramie County, Wyoming for the purpose of this study.

3.1. Data Collection

3.1.1. Smartphone Data Collection

A Samsung S IV smartphone was used to collect the corrugation and roughness data from the test gravel road sections. The mobile device was fixed on the front dashboard using a mobile rack. The smartphone location was chosen to be on the vehicle's front dashboard to limit the generated dust from distorting the captured photos. **Figure 2** shows the mobile setup during the data collection process.

Figure 2. Mobile setup during the data collection.

3.1.2. Corrugation Data Collection

Corrugation can be defined as frequent ripples and grooves form I dry gravel or soil surface as a result from repeated traffic loading. Evaluation of the gravel road corrugation data using the Roadroid application was implemented through a few steps. The process of corrugation rating has been carried out using a developed sophisticated image classifier developed by WYT2 [35]-[37]. First, images of the gravel roads were captured using the mobile camera and the Roadroid mobile application, which was connected to the smartphone's built-in-GPS so that the location of the tested gravel road segments was automatically determined and referenced. Then, the images were uploaded to the Roadroid cloud portal. After that, the analysis was performed and the results were reported. **Figure 3** represents a flow chart diagram for the corrugation data collection and analysis procedure using the Roadroid [37] [38]. However, The Roadroid system follows the PASER rating system for the gravel roads, which is on a scale of 1 - 5. In the PASER rating system 5 is the best and 1 is the worst condition. **Table 2** represents the detailed PASER rating for corrugation [39].

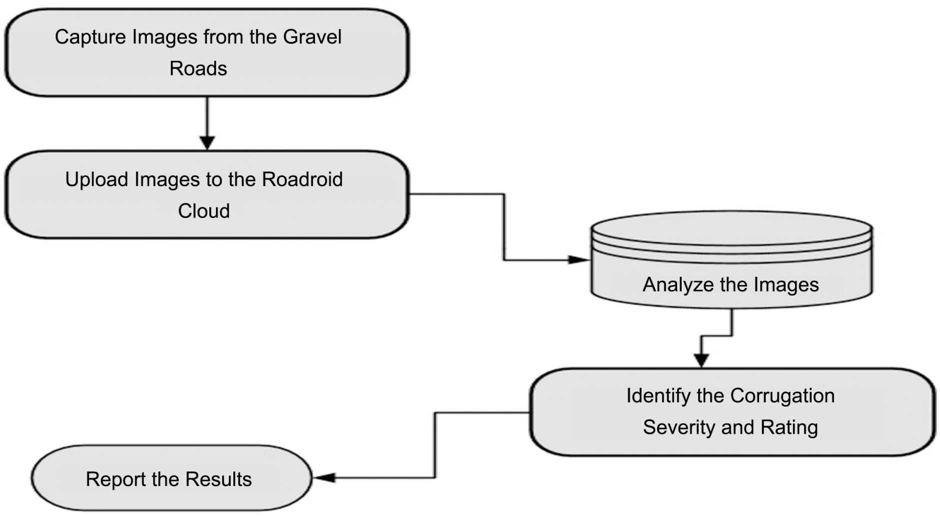


Figure 3. Flowchart for corrugation data collection using roadroid.

Table 2. PASER rating for corrugation.

Surface Rating	Surface Description	Comments
5	Excellent	Excellent Surface, free of corrugation
4	Good	Slight corrugation
3	Fair	Moderate corrugation (1 - 2 in deep)
2	Poor	Moderate corrugation (more than 3 in deep)
1	Failed	Severe corrugation

3.1.3. Roughness Data Collection

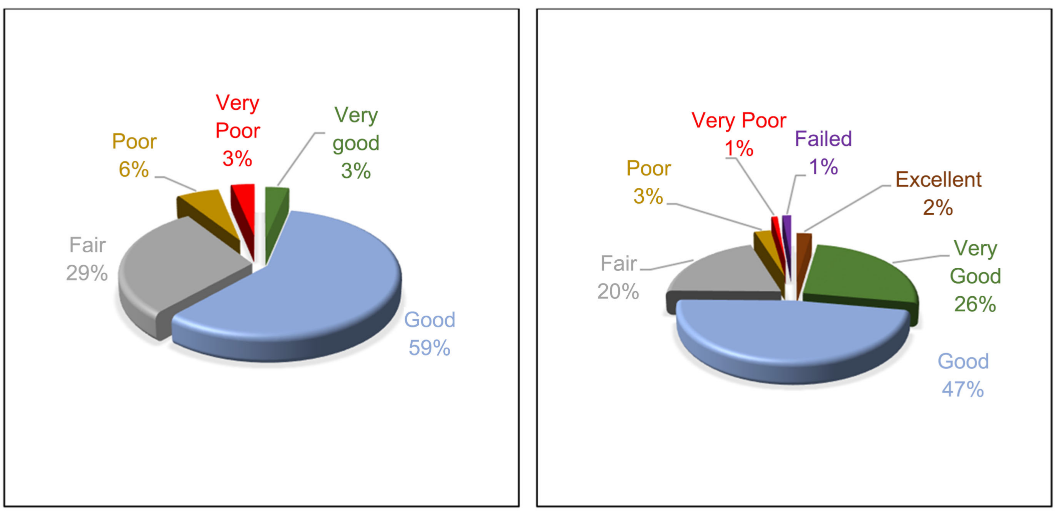
The roughness data was collected using Roadroid. The Roadroid system collects the corrugation data by utilizing the smartphone accelerometer. Roadroid is a response type survey system. It is according to the world banks Information Quality Level 3 (IQL3). A laser survey vehicle is IQL1. IQL3 gives about 80% accuracy in comparison to IQL1. In this method the IRI is estimated by the peak and root mean square vibration analysis. The vibration data was collected using the smartphone, and then a few algorithms are utilized to reflect the vibration data into IRI values. The algorithms were developed based on a car by vibration range between 100 and 200 Hz.

3.1.4. Riding Quality Data Collection

The Gravel Road Rating System (GRRS) manual was used to assign a riding quality rate for each gravel road segment in this study. The implemented rating followed the guidance presented in Table 1. A 4WD Chevrolet Suburban SUV was used to collect the data. This car was chosen because its class is the most used car class in Wyoming. Even though the driving speed was not constant during the data collection, the driver did not exceed any speed limits. The data of this study was collected in the summer of 2020.

3.2. Data Analysis

A statistical descriptive analysis was carried out firstly to get better understanding about the collected data and the condition of the test segments. The corrugation data showed that 61.7% of the segments are in good or better condition and 9.1% of the segment are in poor or very poor condition. Table 3 shows the descriptive analysis for the corrugation data. Table 3 and Figure 4(a) show a detailed descriptive analysis for the corrugation data. In addition, the riding quality assessment showed that 75.23% of the segments are in good or better condition while only 4.91% are in poor or worse condition. Table 4 and Figure 4(b) represent the detailed description analysis.



(a) Corrugation Data (b) Riding Quality Data

Figure 4. Descriptive analysis for the corrugation and riding quality data.

Table 3. Corrugation descriptive analysis.

	Very Good	Good	Fair	Poor	Very Poor
No. of Segments	14	250	125	25	14
% of Segments	3.27	58.41	29.21	5.84	3.27

Table 4. Descriptive analysis for the riding quality data.

	Excellent	Very Good	Good	Fair	Poor	Very Poor	Failed
No. of Segments	10	109	203	85	11	4	6
% of Segments	2.34	25.47	47.43	19.86	2.57	0.93	1.40

Table 3 shows that only 9% of the tested sections were in poor or very poor condition in terms of corrugation. However, having 39 sections in those 2 categories is enough statistically for data analysis and inference purposes. The relationship between the corrugation and IRI data and the riding quality was investigated. Figure 5 shows the scatter plots among the variables between considered variables.

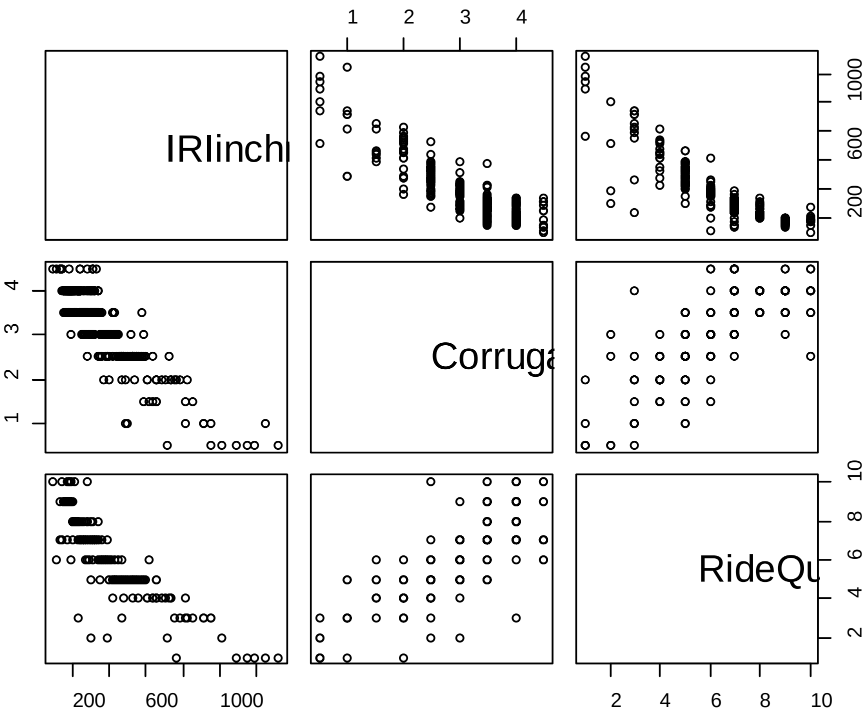


Figure 5. Correlation plots.

In order to develop a computational method predicting the riding quality on gravel roads based on IRI and corrugation conditions, the correlation between the riding quality, IRI, and corrugation was determined using Pearson correlation. A correlation matrix was generated to investigate the significance of the explanatory variable on the model response. This statistical correlation generally measures the dependency between two variables. The correlation matrix as shown in Table 5 demonstrates that there is a high correlation between riding quality and IRI, with a correlation value of 0.878. In addition, there is a significant correlation between riding quality and corrugation with a correlation coefficient of 0.810. Also, the correlation between the explanatory variables was computed and found to be -0.885. Based on statistical limitation, the corrugation and IRI are correlated and the model should have one of them only. The IRI will be kept in the model since its correlation with the ride quality is higher than the corrugation. Based on the scatterplot comparing the IRI data to the riding quality, as shown in **Figure 5**, the IRI data was transformed to Ln (IRI).

Table 5. Correlation matrix.

	IRI	Corrugation	Ride quality
IRI	1.0000000	−0.8850096	−0.8779941
Corrugation	−0.8850096	1.0000000	0.8099385
Ride quality	−0.8779941	0.8099385	1.0000000

Linear regression was utilized in this study to develop a computational method of the riding quality based on the IRI condition. Equation (1) represents the developed model. The coefficient of determination (R^2) for the developed model is 0.8242, which means that the developed model explains 82.22% of the riding quality observations.

$$\text{ERQR} = 27.340 - 3.600\text{Ln}(\text{IRI}) \tag{1}$$

where: ERQR is Expected Rating Quality. IRI is in inch/mile.

The statistical summary for the developed model is shown in **Table 6** which shows that the independent variable is significant. In addition, a residual analysis was carried out to check the model appropriateness. **Figure 6** represents the residual plot for the developed model. The residual scatter plot as shown in **Figure 6** does not have a pattern and the residual points are randomly distributed, which means that the developed model represents the data properly. In addition, Q-Q plot was generated and is shown in **Figure 7**. Basically, Q-Q plot is utilized to evaluate the residuals and to check their distribution. Based on the standardized residual distribution in **Figure 7**, the residual is normally distributed. The existing residual distribution pattern means that the tested data is to peak in the middle.

Table 6. Statistical summary of the model development.

a* F-*Coefficients				
	Estimate	**Std. Error**	**t value**	**Two Tailed P-value**
Intercept	27.340	0.467	58.56	<2 (10 - 16)
Ln (IRI)	−3.600	0.0811	−44.38	<2 (10 - 16)
b Residuals				
Min	**1^{st} Q**	**Median**	**3^{rd} Q**	**Max**
−4.7947	−0.2568	0.0612	0.3898	2.9214

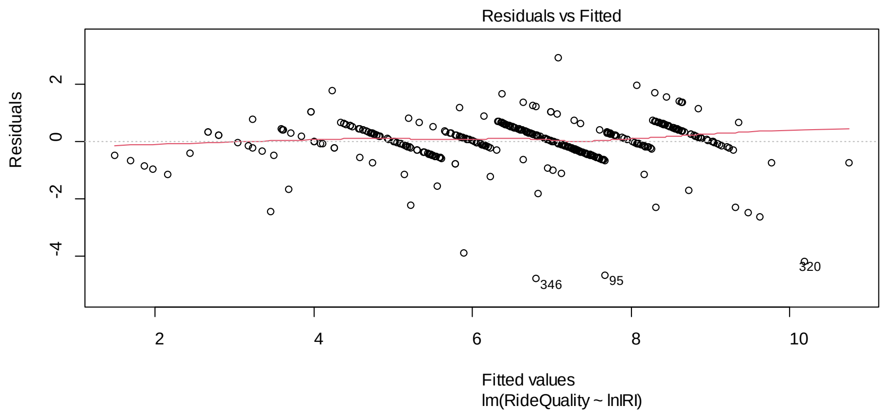


Figure 6. Residual plot for the riding quality model.

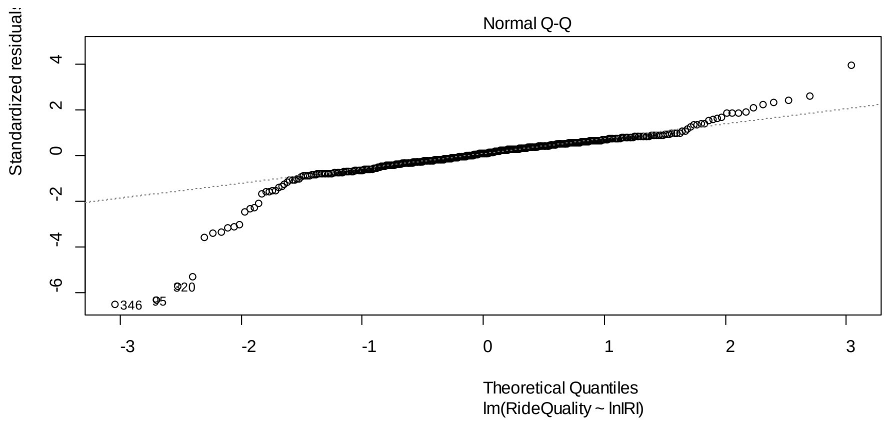


Figure 7. Q-Q plot.

4. ANN Model Development

ANN architecture is one of the most important steps in developing sufficient ANN model. Thus, a massive effort has been spent to determine the suitable architecture. Essentially, developing ANN model includes three main components: the architecture that define the connection between input and output layers, the learning method, and the neuron activation function. The ANN model architecture that used in this study consists of three layers: input layer, hidden layer, and output layer as shown in Figure 8. Extensive literature review and many trails were carried out to determine the optimum neurons number. For the purpose of this study, 10 neurons was found to be the optimum neuron number to achieve the highest accuracy without making the models complicated and time consumers.

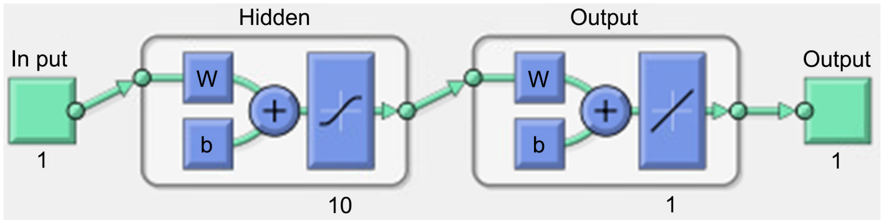


Figure 8. ANN model architecture.

After determining the ANN architecture, MATLAB software was used to analyze the data and develop the prediction models. The available data was randomly divided into two groups: 70% of the data was used to train and develop the model, and the remaining 30% was used for testing and validating the model. The validation and testing set was used to evaluate the models accuracy and reduce the model overfitting. A two-layer feed-forward network trained with Levenberg-Marquardt was utilized in the training process to maximize the models prediction ability by adjusting the connection weights between the layers. Generally, the ANN learning methods are classified into supervised and unsupervised methods. The supervised learning methods depends on the available data to develop inferences about the relations between the input and output variables [40]. The calculated error between the predicted output and the measured values are used to conduct adjustments on the connection weights between the model inputs and outputs. On the other hand, in the unsupervised learning process, the connection weight is adjusted based on stimuli inputs with no desired output provided in order to cluster the input values to similar features [38].

The Levenberg-Marquardt (LM) training method is considered one of the most popular techniques for employing the feed-forward neural networks because of its superior efficiency in enhancing the training precision. This method has been tested on various function approximation problems, and was compared with a conjugate gradient algorithm [34]. Basically, this method consider the neuron as the process basic element. The neuron assumed to have a bias "*b*" related to the input "*n*" and input weight "*w*". The bias can be expressed by Equation (2).

$$a = \sum_{j=1}^{R} w_j p_j + b = Wp + b \tag{2}$$

Newton's method was the base point in developing the Levenberg-Marquardt method, that give the advantage of reducing the nonlinear function sum of squares. This reduction was achieved by optimizing a performance index called F. The complexity in understanding the relationships between variables cause that the ANN models still known as "black box" technique, this complexity increase the difficulties in developing and making inferences about the effect of the individual independent variables on the response variable [15] [39]. This difficulty is considered as a disadvantage in the ANN method comparing to traditional statistical methods. Combination between both ANN and traditional statistical modelling methods, such as linear regression in this study, can limit the weakness and produce a significantly accurate model with proper understanding about the relationships between the considered variables.

The developed ANN model shows a significant high capability in predicting the riding quality on gravel roads based on the IRI condition. The developed ANN prediction model performance were compared to the developed linear regression model. Coefficient of determination (R^2) was used to compare the accuracy among the two methods. The overall R^2 for the developed ANN model is 92.5%; while the R^2 reached 95% during the testing phase. Comparing the R2 of the two developed model shows that adapting the ANN method resulted in a model with

12.5% enhancement in the prediction accuracy. Figure 9 and Figure 10 represent the function fit and model performance, respectively.

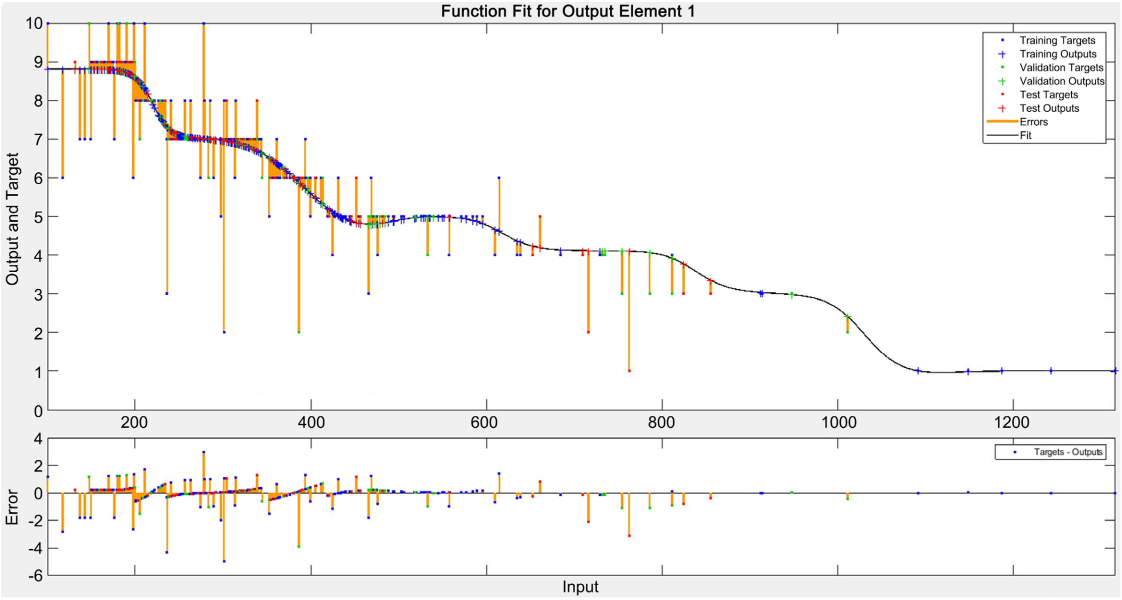


Figure 9. ANN function fit.

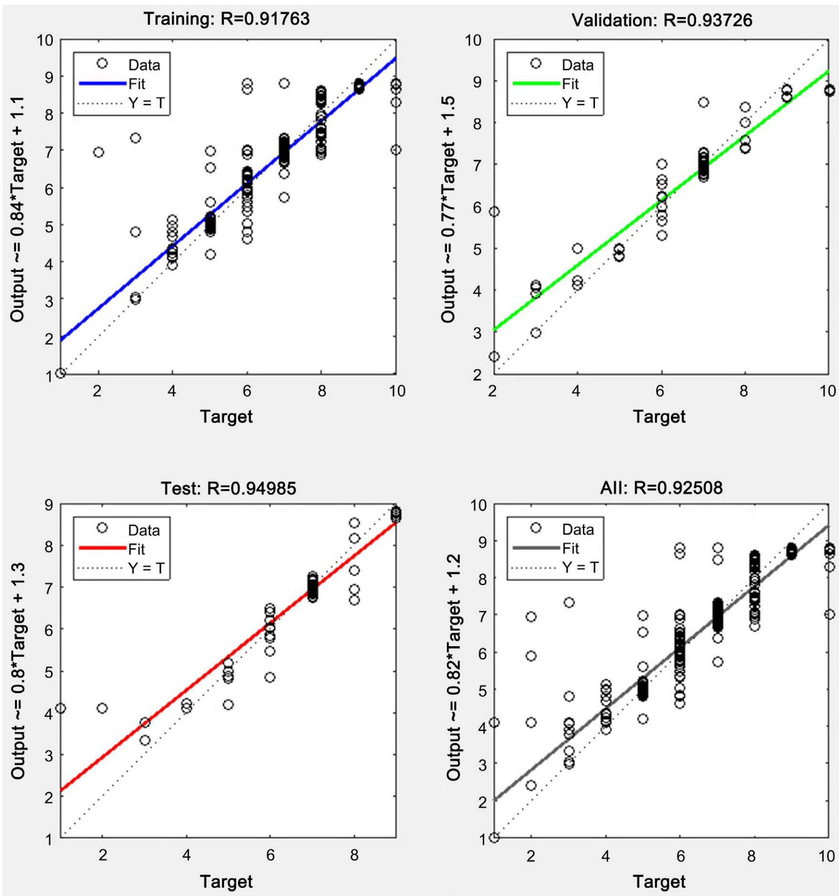


Figure 10. ANN model performance plot.

5. Developing IRI Thresholds for Gravel Roads

Classifying the IRI into multiple categorical groups can significantly enhance the gravel roads maintenance budgeting and planning process. Even though many road authorities have developed their own IRI thresholds for paved roads, there is no suggested IRI threshold for gravel roads in the literature. Gillespie and Paterson described the roughness of different types of roads in terms of IRI and defined IRI ranges for each road type. They stated that usually the rough unpaved roads IRI range is between 507 and 1267 in/mile [33]. **Figure 11** represents the expected IRI ranges in Gillespie and Paterson study [38]. The developed riding quality model, shown in Equation (1), was used to suggest and choose the gravel road IRI thresholds. This study suggests that the IRI could be classified into 3 categories; smooth, acceptable, and rough. In order to suggest a reasonable threshold for IRI on gravel roads the developed linear regression was employed. The linear regression was used to develop an IRI prediction model based on the ride quality. In order to determine the smooth category threshold, the IRI value was calculated using Equation (1) and substituting the ride quality with 7. The substituted valued was 7 for the riding quality since it is the minimum value to have good or better rating as shown in **Table 1**. This means the study assumed that to have a smooth IRI level, a gravel road should have good ratings in riding quality and corrugation. In the same way, the ride quality was substituted by 5, to determine the IRI threshold for the acceptable category. The substituted value was 5 for the riding quality since it is the minimum value to have fair or better rating as shown in **Table 1**. The gravel road section condition will be classified as a poor section in term of roughness when it has riding quality of less than 5. **Table 7** represents the suggested IRI threshold for gravel roads.

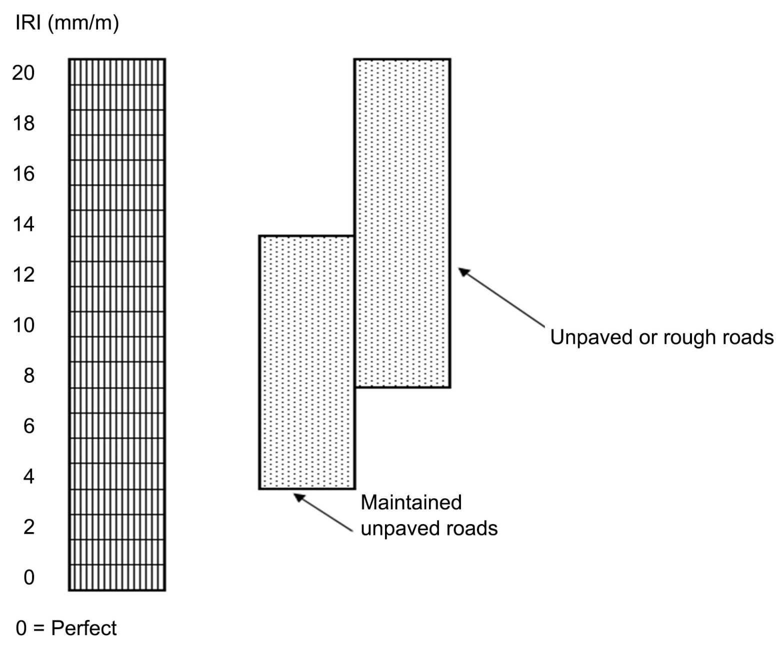


Figure 11. IRI ranges (A world Bank Publication 1990).

Table 7. Gravel roads IRI thresholds.

Condition Category	IRI Threshold (inch/mile)
Smooth	<284
Acceptable	284 - 496
Poor	>496

6. Conclusion

The WYT2 center is in the process of developing a holistic GRMS. One part of the proposed GRMS is developing an integrated fully automated data collection technique. Riding quality is one of the most used terms in GRMS decision-making. Thus, the main goal of this study was to develop a computational method for the riding quality of gravel roads by utilizing a smartphone data collection technique. The developed method can limit subjectivity in the riding quality rating. In addition, this computational method will support local agencies in justifying their gravel road assessment findings. Utilizing smartphones to collect data made the developed computational method practical and cost-effective. In order to develop the computational model for the riding quality, 428 gravel road segments were evaluated and tested. The evaluation results showed that in terms of corrugation, 61.7% of the segments are in good or better condition and 9.1% of the segments are in poor or very poor condition. In addition, the riding quality assessment showed that 75.23% of the segment are in good or better condition and only 4.91% are in poor or worse condition. In conclusion, the developed riding quality model is statistically significant and has the ability to estimate the riding quality using corrugation and roughness data. The coefficient of determination of the developed model is about 82% which is sufficient for the GRMS purposes. Furthermore, thresholds for gravel roads IRI were developed and suggested in this study. There are no such ranges for gravel roads IRI in the literature. The introduced thresholds consider that a gravel road is smooth in terms of IRI if it is less than 295 in/mile, and acceptable if the IRI is between 295 and 509 in/mile, while the road is considered in rough condition if the IRI is more than 509 in/mile.

7. Recommendations

Based on the statistical analysis and results of this study, it is recommended that local agencies implement the developed riding quality model in their gravel roads management systems. In addition, further research efforts should be invested to enhance the developed thresholds for the gravel roads IRI by increasing the number of classes and utilizing advanced mathematical methods such as Tylor's series and Fourier's Series to determine the threshold values.

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Conflicts of Interest

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

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