A Comprehensive Evaluation Study for the Maintenance Management System of Roadways: A Review

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Abstract

Pavement infrastructure is essential and must be protected with limited resources. For decades, industrialized nations have used Pavement Management Systems (PMS) and pavement distress assessment to examine network and project-level pavement conditions. Pavement condition models can anticipate pavement degradation, schedule maintenance, and create multi-year rehabilitation plans based on historical data. Pavement condition surveys are done annually or biannually to calibrate pavement condition models and reduce network maintenance costs. This study highlights road system deficiencies to meet traffic demand, improper systematic methods of maintaining networks, budget constraints for decision makers, deficiencies in road geometrics, poor construction and maintenance practices, the need for proper planning and resource management, and improper planning. The technique comprises a theoretical element of PMS and a review of performance evaluation studies. A PMS lets users export data in an easy-to-understand manner, helping them manage their roadways better. Manual pavement distress surveys need certified raters.

Keywords: *Pavement Management Systems, PCI, PSI, RRMS, Sharp IR-Based Sensor*

1. INTRODUCTION

Road infrastructure maintenance needs condition assessment, performance forecast, program optimization, and strategy formulation. Pavement Management Systems (PMS) were initially used to plan and manage pavements in the 1960s methodically. "Pavement Management Systems" documented 1970s technology developments. Credible data, reasonable performance prediction models, and user-friendly data management tools are essential for PMS implementation. PMS needs pavement data. Regularly collected data helps reflect the network's state, choose maintenance plans, and predict pavement problems [1, 3].

Road surface quality and efficiency affect life, social system health, and economic and commercial continuity. Ageing, usage, and mismanagement may cause highway breakdowns. Roadway upkeep and preservation should be a national priority. Pavement Management improves pavement condition and performance while reducing expenses. Pavement Management Systems PMS are asset management systems for road management [4, 6].

Asset management systems include PMSs. A PMS not only make choices, but also it may help the author comprehend the repercussions of different options. "A Pavement Management System is characterized as the techniques for gathering, dissecting, keeping up, and revealing asphalt information, to help the chiefs discover ideal procedures for keeping asphalts in useful condition over a given timeframe for the least expense". A PMS lets users export data in an easy-to-understand manner, helping them manage their roadways better. Pavement condition models make pavement management systems work. Agency performance measures determine these models. Some pavement condition models use subjective eye examination, quantitative data for particular distresses, or both. Some agencies with limited resources may use models that predict performance based on traffic or time. In contrast, others may use complex indices as a function of material properties, climate, or traffic to collect more detailed pavement deterioration data. The fundamental purpose of any performance model is to estimate the future pavement state for multi-year pavement performance analysis, maintenance and rehabilitation planning, budget allocations, and life-cycle cost estimation [7, 9].

Some of the issues identified in this study are as follows:

1) Inadequate road system to meet traffic demand.
2) Inadequate systematic network maintenance technique.
3) Decision-makers face budget limits.
4) Road geometric deficits.
5) The need for appropriate resource planning and management.

2. STUDY METHODOLOGY

Figure.1 shows the two-stage methodology: First, a theoretical aspect of the pavement management system PMS is introduced, followed by research on performance assessment measurement.

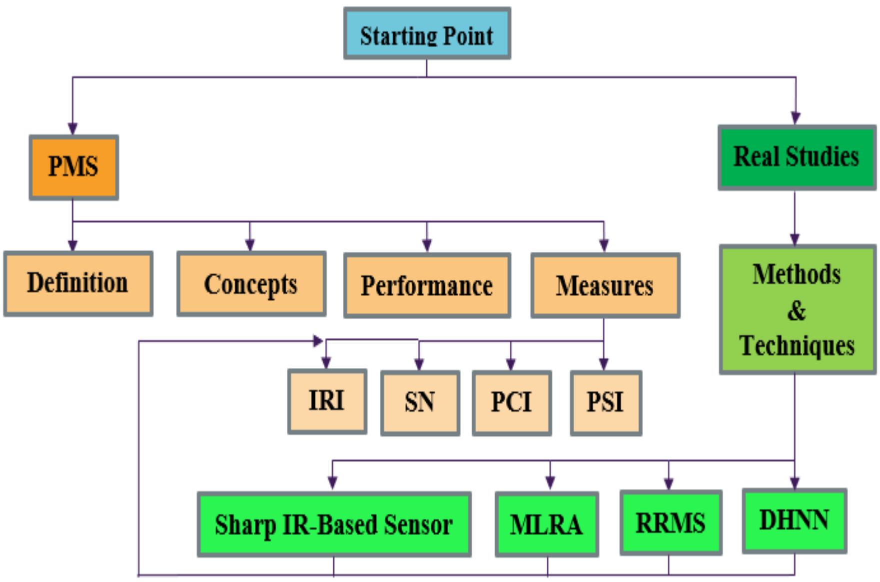

Figure 1. Diagram of the Study Methodology.

3. PAVEMENT PERFORMANCE MEASURES

Pavement performance measurements assist in managing a pavement network by evaluating a pavement segment's condition. Management is context-sensitive; thus, agencies choose their grading system depending on experience. A numerical scale is used to evaluate pavement performance. Pavement management systems use pavement condition indexes to trigger rehabilitation options, assess network conditions, estimate maintenance and rehabilitation costs, and monitor pavement-type performance [9].

The Present Serviceability Index (PSI), the Pavement Condition Index (PCI), the Structural Number (SN), and the International Roughness Index (IRI) are some of the most widely used evaluation systems.

3.1 The Present Serviceability Index (PSI)

Figure. 2 shows the Present Serviceability value (PSI) of American Association of State Highway and Transportation Officials' (AASHTO) [10]. A 0–5 value based on a part of "expert" subjective evaluations of pavement conditions. A pavement with a PSI below 2 to 3 may need repair, rehabilitation, or other maintenance. The above Pavement Design Guide approach (new design and overlay) uses PSI since the design equations define the link between PSI and traffic load (Equivalent Single Axle Load) or time [11].

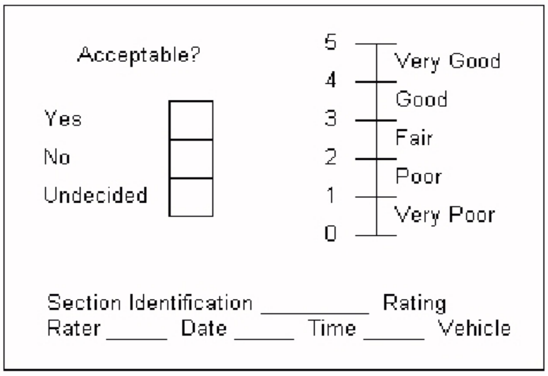

Figure 2. Individual PSI Rating-Form [11].

3.2 The Pavement Condition Index (PCI)

This approach provides a more in-depth review of a pavement section to remove the subjectivity rating. The ASTM D6433 [12] standard and custom PCI rating scale is shown in Figure. 3; this approach is useful because it allows for the quantification of major distresses, which in turn may trigger various rehabilitation programs based on the intensity and kind of distress [11].

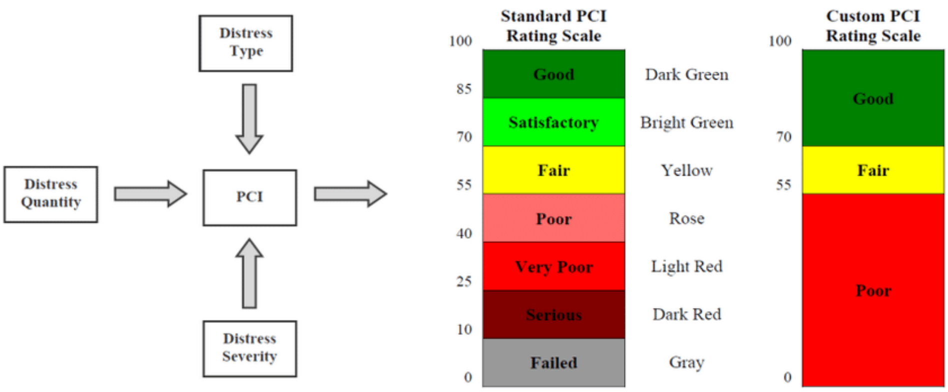

Figure 3. The Standard and Custom PCI Rating Scale [12].

3.3 The Pavement Structural Number (SN)

Structural number (SN) is usually assessed using the falling weight deflectometer (FWD) or rolling weight deflectometer (RWD). SN specifies pavement structural requirements for the planned traffic load. The 1993 AASHTO Guide for Design Pavement Structures provides a methodology to calculate pavement's remaining service life from the effective pavement structure modulus based on FWD deflection and load measurements. Figure. 4 illustrates the role of SN within the PSI. Pavement effective modulus calculates structural numbers and predicts structural service life. SN may be experimentally computed in addition to FWD based on structural layer distresses, thickness, and drainage. Project-level SN is used to compute pavement overlay layer thickness for traffic loads. More network-level PMS agencies are using structural number indexes [13].

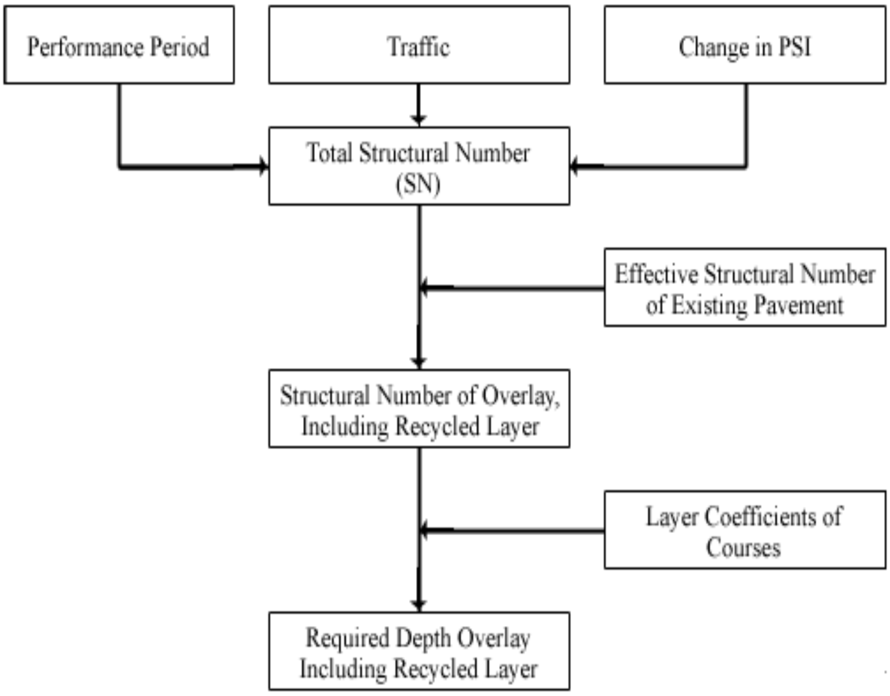

Figure 4. An Example illustrates the role of SN within the ΔPSI [13].

3.4 The International Roughness Index (IRI)

There are a variety of methods and indices that have developed over the years to assess ride quality; the IRI, in Table 1, is defined as a "scale for roughness based on the simulated response of a generic motor vehicle to the roughness in a single wheel path of the road surface". Ride quality measures the state of the pavement directly to indicate how well a road performs in terms of user comfort and satisfaction [13].

Table 1. IRI Condition Criteria [13].

IRI scale (in/mi)	Description
<=60	Very Smooth
61 – 120	Smooth
121 – 170	Fair
171 – 220	Rough
>=220	Very Rough

4. REVIEW OF CASE STUDIES

An overview of the literature on pavement maintenance management systems is provided, and all relevant works are referenced at the conclusion of the cases for further study. Some previous case studies on the subject were collected and analyzed.

4.1 Using the Discrete Hopfield Neural Network (DHNN)

This study found that many optimized indexes and grading standards that reflect functional performance and structure of the pavement comprehensively evaluate pavement performance due to the index's deficiency and the specification's evaluation method defect [14]. The discrete Hopfield neural network has a straightforward design, fewer training samples, and perfect impartiality. MATLAB builds the DHNN to assess test pavement. After simulating and learning, the neural network evaluates the ideal cement pavement performance grading index matrix and six unclassified test pavement evaluation index matrices. Finally, the discrete Hopfield neural network assessment approach is trustworthy compared to the fuzzy complex matter element and the nonlinear fuzzy method. The study uses discrete Hopfield neural networks to evaluate cement pavement performance. This approach is objective and requires fewer training samples than the previous method. Using test section data, the discrete Hopfield neural network technique assessed cement pavement performance. The discrete Hopfield neural network technique outperforms complex fuzzy elements and nonlinear fuzzy methods. American physicist J.J. Hopfield proposed Hopfield neural network in 1982. The Hopfield neural network and learning method are binary. Discrete Hopfield neural network classification learning involves progressively approaching the evaluation index of the typical classification level to the equilibrium point of DHNN. Neurons produce 1 or -1, signifying activation or suppression. Thus, DHNN. Figure 5 shows a discrete Hopfield neural network with three neurons. Layer 0 is an input to the network, not neurons. The first layer neuron sums the input and weight coefficient product and processes it with the nonlinear function f to obtain output information simple threshold function f. If the neuron's output is above the threshold, it outputs 1. Neuron output is -1 if it is below the threshold.

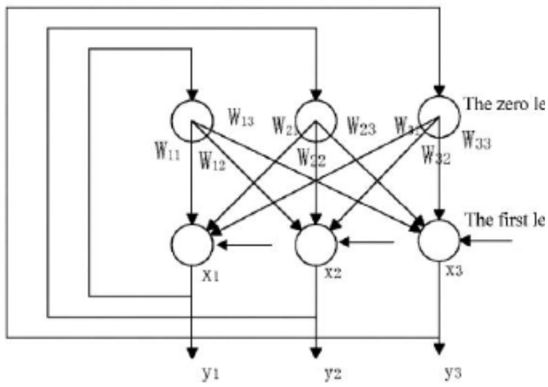

Figure 5. Structure of Discrete Hopfield Neural Network (DHNN) [14].

This study uses MATLAB's discrete Hopfield neural network to evaluate the test section pavement. It concludes:

1) The study enhances the Code's cement pavement performance assessment indicator selection. Seven optimization metrics from the literature assessed pavement performance and structure. This is crucial to assessing pavement performance.

2) The discrete Hopfield neural network pavement performance assessment technique is more straightforward than BP and radial basis neural networks. This technique directly uses the MATLAB neural network toolbox, requiring a few training examples. This test-saving strategy is objective. The assessment

findings are accurate and scientific since the DHNN approach is like the fuzzy composite matter element method and the nonlinear fuzzy method.

4.2 Using a Cost-Effective Sensor-Based Monitoring System

The study finds that Pavement management systems rely on pavement condition data. Automated data gathering is safer, faster, more consistent, and repeatable [15]. The expensive gadgets needed for automated data collecting are a drawback. An innovative, cost-effective, and accurate automated data-gathering system is needed. Pavement roughness is a crucial indicator of pavement condition and ride quality. This project aims to create automated, low-cost roughness measurement equipment. Pavement roughness is measured using an additional wheel with accelerometers and a GPS. A linear model with an R^2 of 0.87 calculates the International Roughness Index using longitudinal profiles. Root-mean-square error (RMSE) is 10%, and the average error percentage (AEP) is 20%. First, the road roughness monitoring system (RRMS) was designed and collected data. After data collection, digital signal processing was used to extract acceleration data related to pavement roughness in the second step. The road's longitudinal profile was measured using vibrational responses. The optimal problem-solving technique retrieved the RRMS dynamic equations and parameters. The longitudinal profiles of the analyzed trajectories were adjusted for a specific vehicle speed. Spectral analysis of obtained data verified the system research approach. After extracting the data, statistical analysis was used to compute the IRI from the longitudinal profile of the investigated route to test RRMS output accuracy and system performance. After validation, system output repeatability was assessed. In this study, a one-degree-of-freedom mechanism was used to develop a pilot RRMS with a solid rubber wheel with a diameter of 30 cm and a thickness of 4 cm and steel profiles (unsprung mass) connected to the vehicle by a hinge joint to fix the mechanical system. The hinge joint allowed the equipment to spin in the y-direction (pitch rotation) to measure vertical arch roughness and topical pavement roughness. The vibration was less impacted by unevenness despite device rotation. The machine rotated in the z-direction (yaw rotation) to avoid wheel slippage on the pavement. Twisted steel profiles attached the RRMS to the chassis. Figure. 6 shows the machine schematic without changing the mechanical system.

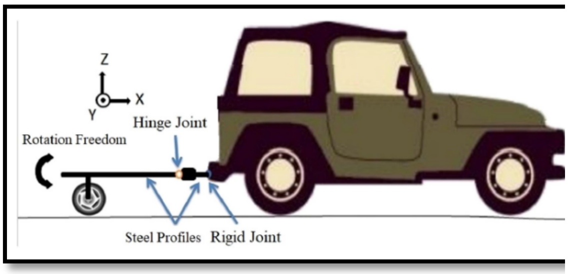

Figure 6. The Schematic of RRMS [15].

The RRMS measured vibrational response. Figure. 7 shows the research equipment. To monitor road roughness-induced vibrations from the vehicle to the RRMS, one accelerometer module was mounted on the fifth wheel's centre axis and the other at the system-vehicle junction. Figure. 8 shows the RRMS with the fifth wheel's central axis microcontroller board.

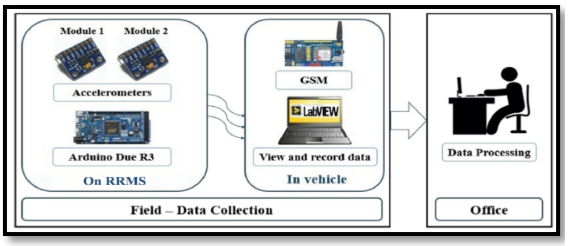

Figure 7. Flowchart of the equipment used in RRMS [15].

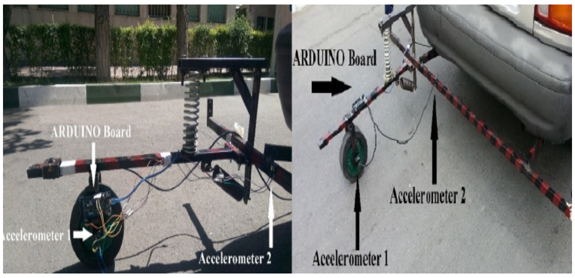

Figure 8. RRMS Connected to the Vehicle [15].

After equipping the RRMS with two accelerometer modules and a microcontroller board, data was collected using an Arduino program and LabView code utilizing the I2C connection protocol. Pavement management relies heavily on pavement condition data collecting. Pavement assessment depends on roughness. Pavement management systems need cost-effective road roughness data collection methods. This project developed a low-cost Road Roughness Monitoring System (RRMS) using an accelerometer on a vehicle's extra wheel to monitor pavement roughness. The system's pavement roughness calculation mistakes are RMSEn of 10% and AEP of 20%. This research achieved the following:

1) The design and development of a revolutionary and cost-effective system without unsprung mass and damper placed on a solid rubber fifth wheel to monitor longitudinal road profile and compute IRI.
2) Determining the RRMS dynamic parameters without hardware testing and deriving the best system dynamic parameter responses by comparing two particle swarm optimization PSO and genetic algorithm GA approaches.

4.3 Using of Multiple Linear Regression Analysis (MLRA)

This study examined how Truck and Other Heavy Vehicles (CVPD), California Bearing Ratio (CBR), precipitation, pavement age, and thickness affect deflection and the International Roughness Index (IRI) [16]. Then established, predictive variables for Rwandan pavement performance assessment and assessed their association. Precipitation and CBR predict Rwandan flexible pavement deflection and IRI. Precipitation closely correlates with CBR. Thus, climatic input precipitation predicted Rwandan pavement performance better. Temperature and Pavement Condition Index (PCI) data should be collected and compared to precipitation and CBR results to improve Rwanda's pavement performance assessment decision-making and program development. It uses multiple linear regression to create a Rwandan pavement performance rating model. Multiple regression analysis is a regression with several predictors (x variables). Multiple regression studies how numerous independent or predictor factors affect a dependent or criterion variable. General linear regression as shown in Eq. (1):

$$Yi = \varepsilon_0 + \varepsilon_1 Xi_1 + \varepsilon_2 Xi_2 +. \varepsilon_{(n-1)} Xi_{(n-1)} + . . \varepsilon i \quad \text{Eq 1}$$

Where i = 1, 2, …, n

The study uses Xi=predictors (CVPD, subgrade precipitation, pavement thickness and age). Predictors were selected from Rwanda Transportation Department Agency (RTDA) data; Y=response variables (IRI and deflection).

Rwanda's NR1 from Kigali to Akanyaru is the study's network. Sixteen pavement portions sampled 127.03 km of this highway network. The RTDA conducted a geotechnical study and destructive and non-destructive testing of the existing pavement. Potholes, longitudinal cracking, fatigue alligator cracking, and rutting are structural distresses that gradually weaken pavements. IRI-predictor variable correlations vary from 0.01 to 0.582. Precipitation predicts IRI best ($r = 0.582$, $p < 0.01$). Some predictor factors correlate strongly. CBR highly correlates with precipitation (r =0.514, p < 0.01). Age and CBR have a little link with CVPD. Finally, pavement age reduces IRI. Figure. 9 compares the standardized residual's CDF to the normal distribution's CDF. The residuals were normalized, not the predictors.

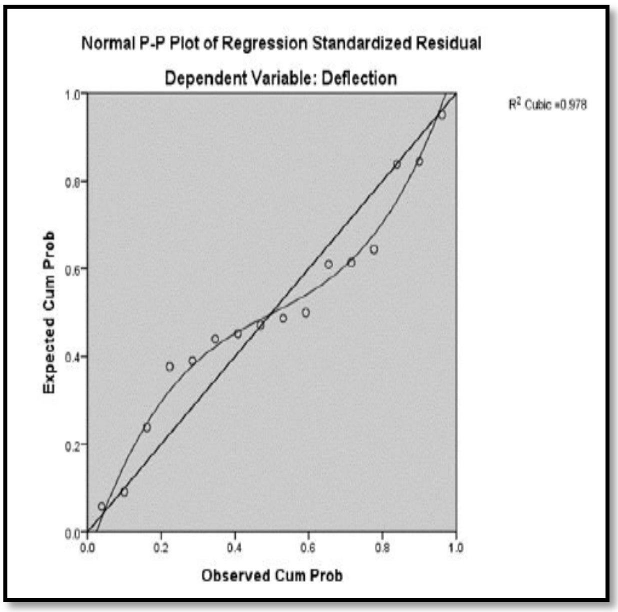

Figure 9. Normal P-P Plot and Histogram of Regression Standardized Residual [16].

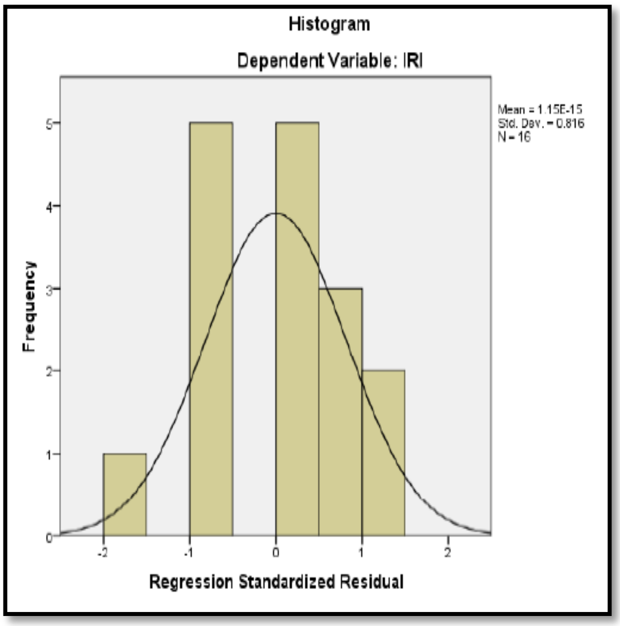

Figure 10. Normal P-P plot and histogram of regression standardized residual [16].

Figure. 10 shows it is close to normal and has more residuals at zero than predicted. A pavement maintenance management system helps choose, assess, and maintain pavements. The study's conclusion was:

1) Climate input precipitation predicted Rwandan pavement performance better. Further investigations compare temperature data.

2) IRI decreased with pavement age and thickness. Rwandan pavement performance is statistically affected by soil subgrade CBR.
3) More inventory and condition data for the Rwandan pavement management database are needed to manage road infrastructure. It must be objective, reliable, and repeatable.
4) To improve Rwandan pavement performance, pavement maintenance and rehabilitation decision-making must be incorporated into an annual management cycle of planning, budgeting, engineering, and execution.

4.4 Using of Sharp IR-Based Sensor

The study finds that maintaining degraded pavement on time reduces life cycle expenses. Pavement condition data including road roughness guides maintenance and repair [17]. Due to data gathering costs and low importance, low-volume highways are seldom monitored. Road users travel extensively. This work develops an affordable data collecting system using a Sharp IR-based sensor and an accelerometer to record pavement profile and estimate roughness index for low-volume highways.
This research includes data management, gathering, analysis, and study design. The device measures pavement roughness of uneven roadways with 87.4% accuracy at 30 km/h. It may replace costly data-collecting trucks. Modules for this study follow the literature review. The research design included pavement roughness index and measurement technique selection, sensor selection, and DAS conceptual design. Data management included DAS creation and data collection, storage, and preprocessing software. Data acquisition followed, including experiment design, data collection, and quality control. Finally, the road roughness index was calculated using DAS data and ground truth to verify and confirm findings. Figure. 11 depicts the study technique. Data management began with DAS development after conceptual design. Figure. 12 The study's voltage transformation model development was covered and uncovered, as illustrated in Figure. 13. Table 2 shows model statistics. Each condition has the lowest SSE and RMSE and the highest R^2 and R^2Adj. Validation SSE and RMSE were also good. Researchers have created a sharp IR-based cost-effective sensor that might evaluate road roughness as an indication of pavement quality.
This research included study design, data administration, data gathering, and analysis. The study design included a roughness index, sensor, and data-gathering system conceptual design. Data management involves system and software development to acquire and preprocess data. Data acquisition included experiment design, data collecting, and quality control. The pavement roughness index was calculated using system and ground truth data.

Table 2. Best Models Statistics [17].

Light condition	Goodness of fit				Validation	
	SSE	RMSE	R^2	R^2_{Adj}	SSE	RMSE
Covered	0.6633	0.1487	0.9995	0.9995	0.7505	0.2612
Uncovered	0.2136	0.0830	0.9998	0.9998	0.3054	0.1666

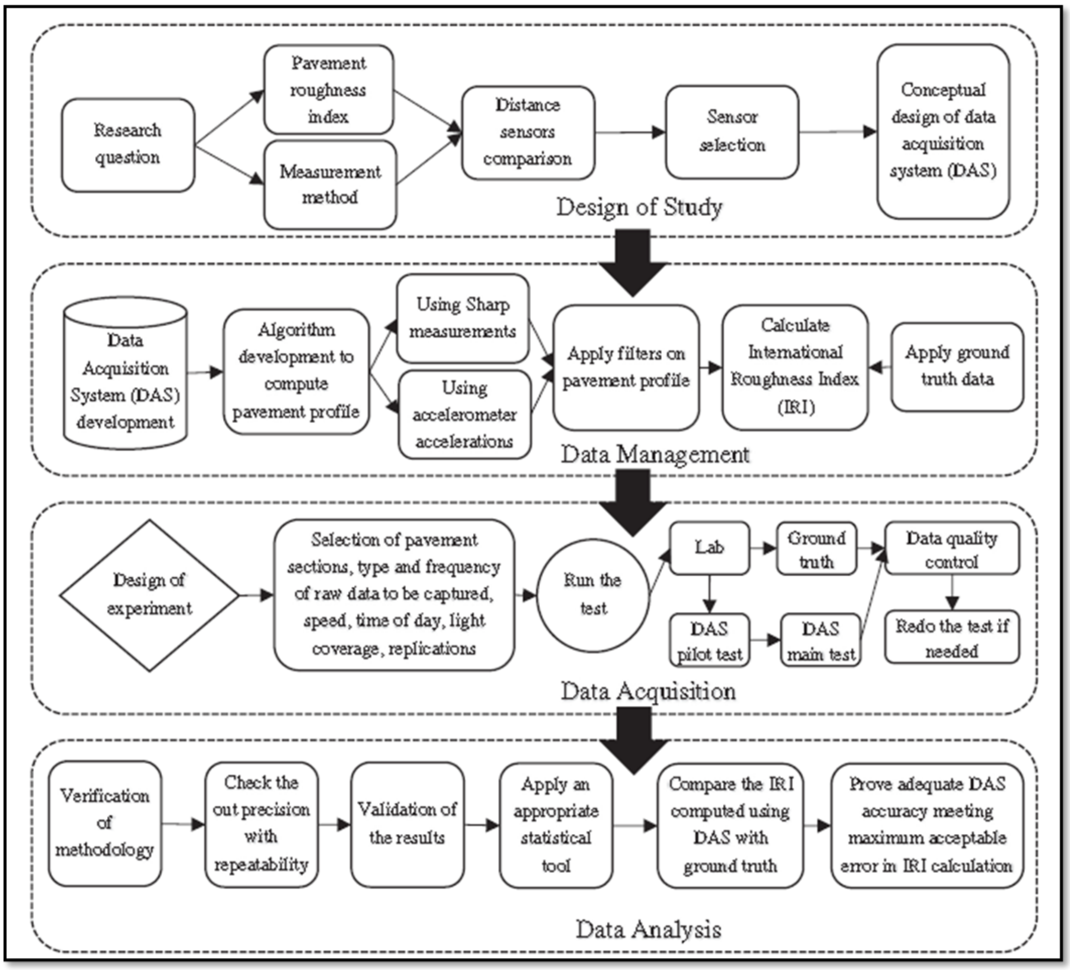

Figure 11. The Sharp IR-Based Sensor Study methodology [17].

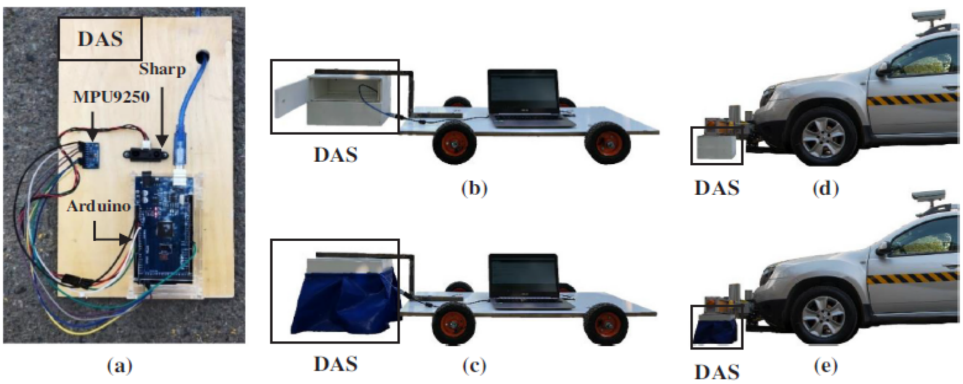

Figure 12. The Development of the DAS: (a) DAS on a wooden board (b) Kart without DAS Coverage (c) DAS-equipped kart (d) A vehicle used for data collecting without DAS coverage. (e) A vehicle for data collecting with DAS coverage [17].

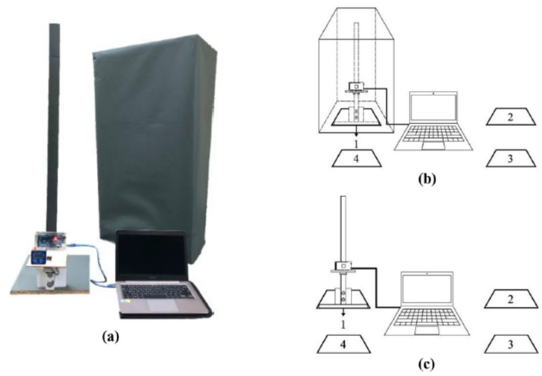

Figure 13. Development of a voltage transformation model (a) Box with Fabric Cover (a) Data collecting plan for the mentioned circumstance (c) A plan for gathering data in an uncovered situation [17].

The study's voltage transformation model development was covered and uncovered, as illustrated in Figure. 13.

Study models convert voltage to distance under covered and uncovered settings for smooth and uneven surfaces, as illustrated in Figure. 14. in Figure. 15 shows IRI's model verification. This type of road is heavily used. Figure. 15 shows IRI's model verification. This type of road is heavily used.

Figure 14. Pavement sections surveyed for verification testing: **(a)** Smooth section. **(b)** Rough section [17].

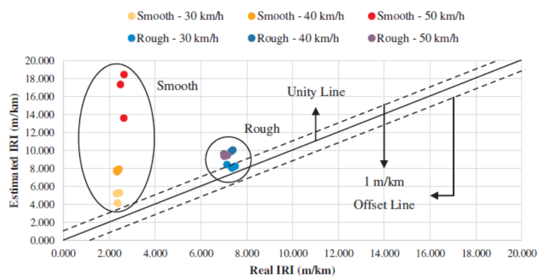

Figure 15. Estimated IRI versus Real IRI [17].

This work improved system output verification and validation:

1) A 0.8%-accurate model estimated the Sharp sensor's distance from the pavement. Preprocessing accelerometer readings required a Fast Fourier Transform filter.
2) The pilot test data collecting system estimated pavement roughness at 10 km/h with a 3% inaccuracy.
3) The suggested method assessed uneven road surface roughness with 87.4% accuracy at 30 km/h.

5. CONCLUSION

The study summarized the following points:

1. A PMS outputs information in an easy-to-understand manner, helping users manage their roadways better. Manual pavement distress surveys need certified raters.
2. Discrete Hopfield neural network pavement performance assessment is extensive. The more complete the cement pavement performance assessment indicators, the more accurate the grading standards under each evaluation index (the more accurate the equilibrium point of the discrete Hopfield neural network). DHNN's assessment approach is comparable and more accurate.
3. Filtering acceleration signals from the RRMS and vehicle using new digital signal processing algorithms to derive initial road longitudinal profile data.
4. A pavement maintenance management system helps choose, assess, and maintain pavements. Precipitation and CBR predicted deflection and IRI.
5. Timely planning reduces pavement life cycle expenses. Pavement monitoring often uses expensive data-gathering vehicles. Since monitoring low-volume highways is expensive, they often need to be addressed. A Sharp sensor and accelerometer created a low-cost data-

collecting device to record pavement profiles and estimate the roughness index for low-volume roads.

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