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Pavement Condition Assessment Using Pavement Condition Index and Multi-Criteria Decision-Making Model

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Abstract: Road maintenance is essential to the growth of the transportation infrastructure and, thereby, has a big impact on a nation's overall economic stability and prosperity. It is impossible to simultaneously monitor and maintain the entire network. As a result, transportation authorities are eager to develop scientific foundations for assessing the importance of maintenance tasks within the network of roads. Hence, pavement assessment methods are needed to establish the priorities and achieving the most convenient level of service. In this study, a road stretch was assessed using the sixteen criteria in the Distress Identification Manual for pavement defects, using pavement condition index (PCI) and multi-criteria decision-making models (MCDM). The two methods were compared to determine the possibility of using MCDM. The study came to the conclusion that MCDM is reliable in assessing pavement performance because both methods indicated that the road pavement is deteriorating.

Keywords: Pavement condition index (PCI); Multi-criteria decision-making models (MCDM); Grey theory; Combined compromise solution (CoCoSo)

1. Introduction

Prioritizing road reconstruction and maintenance requires careful consideration of pavement performance [1]. Experts can determine the best maintenance planning and pick the optimal installation method through precise evaluation and accurate defects estimation [1]. An assortment of observed factors regarding the structure and surface quality of the pavement has an impact on how well it is maintained [2]. Roads deteriorate as a result of the interaction between weather, traffic volume, and traffic type. Establishing a trustworthy foundation for performance assessment is therefore crucial to examining how the aforementioned factors affect pavement structural behaviour [3].

Roads sustain damage and suffering throughout their service life [4]. Therefore, regular road surface maintenance, including inspection and repair, is essential to maintaining pavement quality, extending pavement life, and maintaining the usefulness of roadways. The most frequent surface flaws include surface imperfections, surface deformation, and cracking [5]. The initial survey is a crucial first step in creating an effective maintenance management system, where the information gathered is used to inform correct and economical decisions that support maintaining network sufficiency [6].

To document the type, severity, and number of distresses based on visual inspection, a thorough survey of defects is conducted. Later, using performance evaluation models, the data gathered is applied to assess the pavement condition. Various techniques have been developed throughout the years to more accurately assess the performance of road pavement. One of the most well-known models in the field is the pavement condition index (PCI). The evaluation result is a numerical indicator with a range of zero for damaged surfaces to one hundred for perfect conditions [7].

This paper investigates a heavy traffic road in the city of Misurata, Libya to evaluate its pavement condition. Two approaches were adopted, namely, pavement condition index (PCI), and Multi-criteria decision-making models (MCDM). PCI is based on information gathered by two qualified engineers regarding faults of certain road segments. MCDM, on the other hand, is based on distributed survey interviews on four experts with more than fifteen years of experience in the transportation industry.

The purpose of the study is to investigate whether MCDM can be used to assess pavement performance. A comparison of the results between MCDMs and PCI was carried out to spot differences and assess the accuracy and reliability of the results.

2. Literature Review

For transportation agencies across the world, it is a critical task to keep a dependable Pavement Management System (PMS). A country's economic progress is significantly impacted by the expansion of its road network. Pavement surface continues to deteriorate over time unless suitable rehabilitation is provided due to traffic loading, daily and seasonal climate fluctuation, and other factors. Therefore, in order to preserve the pavement, periodic monitoring of the status of the pavement is required, and this monitoring must be followed by rapid treatment [8]. Several transportation bodies have created rules and policies to preserve the road network. The policies contain steps for evaluating the system's pavement condition, and choosing when to apply the optimal maintenance option.

The evaluation of pavement condition using pavement performance indices is a crucial part of any PMS. Numerous indices, including the pavement condition index (PCI), the international roughness index (IRI), the pavement serviceability rating (PSR), etc., have been widely adopted [9]. Pavement performance models are needed to assess the status quo and forecast the performance of the pavement sectors. It is necessary to collect information on the state of the pavement, identify the factors that contribute to pavement degradation, and then choose the mathematical model that best illustrates the relationship between the pavement conditions and the identified factors [10].

In the United States and Canada, the PCI method is a frequently used instrument for evaluating asphalt and concrete pavements. Detailed field survey data that reflect the pavement's present condition is employed to calculate PCI. In a typical field survey, the pavement surface distresses are fully described and measured using either eye inspection surveys or image-based surveys [10].

The accuracy of pavement performance prediction models is greatly affected by the availability of distress data. Grey models (GM) are found to be intuitive, flexible, able to handle sudden changes in parameters, and only need a small number of data points to update predictions [11]. Over the past few decades, many studies have been undertaken with GMs in the field of pavement management.

To forecast pavement conditions, Kouyate created a trigonometric GM and compared the results with a first-order GM and two S-shaped nonlinear models. The results revealed that the proposed trigonometric model performed better than the other two models [10].

With the aid of GM (1,1) models, Zhang et al. [12] calculated the rutting, skid resistance, and smoothness of the pavement. To gauge how well their model performed as compared to field-measured data, they employed residuals and grey absolute correlation as measures, and discovered that the GM (1,1) has a high level of accuracy.

Based on a weighted function of the four components PCI, riding quality index, rut depth, and skid resistance index, Yu et al. [13] created a new pavement quality index (PQI), and proved that GM (1,1) and grey relational analysis can be used in specific situations.

Using a multivariate GM, Du and Shen [14] developed a model that predicts rut depth (1,2). The model was successful in forecasting rut depth.

Regarding the prediction of traffic characteristics, Bezuglov et al. [11] and Gurcan et al. [15] looked at three grey models and contrasted them with nonlinear models. Lower prediction errors and better accuracy were achieved by grey models.

Wang et al. [16] combined grey relation analysis (GRA) and support vector machine regression (SVR) to predict asphalt pavement performance. GRA was employed to identify important characteristics influencing pavement performance, and SVR was utilized to anticipate pavement performance with those factors. The model was implemented to forecast the rutting depth index. Compared to other models, GRA-SVR was proved to be accurate and time-independent, despite being rather complex.

3. Methodology

The U.S Army Corps of Engineers developed the PCI method for the aim of pavement condition evaluation [6]. PCI is a numerical rating of the pavement condition that ranges from 0 to 100 with 0 being the worst possible condition and 100 being the best possible condition [17]. The pavement to be evaluated is divided into branches, which are then further divided into sections. Each section is split into sample units. Visual evaluation of pavement sample units determines the kind and severity of pavement deterioration [18]. The quantity of the distress is measured accordingly and the PCI is determined for each sample unit. Based on the PCI of the examined sample units inside the section, the PCI of the pavement section is calculated following steps on Figure 1 [17].

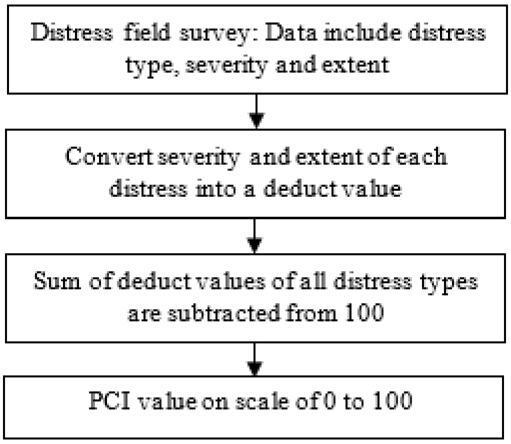

Figure 1. Pavement condition index calculation flowchart

PCI numerical values are converted to verbal rating that describes the condition of the pavement surface varies from "failed" to "excellent". The upper part of the scale indicates pavement with minor defect and requires regular maintenance. Pavement on the lower part of the scale requires major rehabilitation or reconstruction.

The use of multi-criteria decision methods has steadily increased in recent years. There are many applications that use these methods, such as the applications in the field of logistics [19, 20], transportation [21, 22], financial [23]. One of the methods used is Grey System Theory, introduced by Deng in the early 1980s [24], which focuses on solving problems with incomplete information or small samples. Hence, it generates and extracts useful information from the available data. This paper is based on a hybrid Grey-COCOSO methods. COCOSO model was created by Deng [25] in 2019. The calculation is created using macros developed with MS Excel software. The steps of the proposed method are as follows:

The Grey-COCOSO model consists of the following steps:

Step 1: Selecting the set of the most important attributes, describing the alternatives.

Step 2. Determine the attribute weights: Attribute weight W_j can be calculated as follows:

$$\otimes W_j = \frac{1}{K}\left[\otimes W_j^1 + \otimes W_j^2 + \cdots + \otimes W_j^K\right] \tag{1}$$

$$\otimes W_j^K = \left[\underline{W_j^K}, \underline{W_j^K}\right] \tag{2}$$

Step 3. Alternatives evaluated by the decision makers: decision makers use linguistic or verbal variables when evaluating alternatives according to various criteria.

$\otimes G_{ij}^K, (i = 1,2,\ldots,m; j = 1,2,\ldots,n)$is the attribute value given by the kth decision maker to any attribute value of the alternative. In grey system this value is shown as, $\otimes G_{ij}^K = \left[\underline{G}_{ij}^K, \overline{G}_{ij}^K\right]$ and computed as:

$$\otimes G_j = \frac{1}{K}\left[\otimes G_j^1 + \otimes G_j^2 + \cdots + \otimes G_j^K\right]$$

Step 4. The construction of Grey Decision Matrix:

$$G = \begin{bmatrix} \otimes G_{11} & \otimes G_{12} & \cdots & \cdots & \otimes G_{1n} \\ \otimes G_{21} & \otimes G_{22} & \cdots & \cdots & \otimes G_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \\ \otimes G_{m1} & \otimes G_{m2} & \cdots & \cdots & \otimes G_{mn} \end{bmatrix} \tag{3}$$

Step 5. The normalization of Decision Matrix:

$$D^* = \begin{bmatrix} \otimes G_{11}^* & \otimes G_{12}^* & \cdots & \cdots & \otimes G_{1n}^* \\ \otimes G_{21}^* & \otimes G_{22}^* & \cdots & \cdots & \otimes G_{2n}^* \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \\ \otimes G_{m1}^* & \otimes G_{m2}^* & \cdots & \cdots & \otimes G_{mn}^* \end{bmatrix} \tag{4}$$

For a benefit attribute $\otimes G_{ij}^{*}$ is expressed as:

$$\otimes G_{ij}^{*} = \left[\frac{G_{ij}}{G_j^{max}}, \frac{\overline{G}_{ij}}{G_j^{max}}\right]$$

where, $G_j^{max} = max_{1<i<m}\{\overline{G}_{ij}\}$ and for a cost attribute $\otimes G_{ij}^{*}$ is expressed as

$$\otimes G_{ij}^{*} = \left[\frac{G_j^{min}}{\overline{G}_{ij}}, \frac{G_j^{min}}{\underline{G}_{ij}}\right]$$

where, $G_j^{min} = min_{1<i<m}\{\underline{G}_{ij}\}$.

Step 6. Weighted Normalized Grey Decision Matrix normalized D^* matrix is weighted by the

$$\otimes V_{ij} = \otimes G_{ij}^{*} X \otimes W_j$$

Process which establishes the weighted normalised grey decision matrix D_W^*.

$$D^* = \begin{bmatrix} \otimes G_{11}^{*} & \otimes G_{12}^{*} & \cdots & \cdots & \otimes G_{1n}^{*} \\ \otimes G_{21}^{*} & \otimes G_{22}^{*} & \cdots & \cdots & \otimes G_{2n}^{*} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \\ \otimes G_{m1}^{*} & \otimes G_{m2}^{*} & \cdots & \cdots & \otimes G_{mn}^{*} \end{bmatrix} \tag{5}$$

Step 7: The total weighted comparability sequence (S_i) and the sum of the weighted comparability sequences (P_i) for each alternative are calculated as follows:

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij}\right) \tag{6}$$

This S_i value is achieved based on grey relational generation approach:

$$P_i = \sum_{j=1}^{n} \left(r_{ij}\right)^{w_j} \tag{7}$$

Step 8: Relative weights of the alternatives using the following aggregation strategies are computed. In this step, three appraisal score strategies are used to generate relative weights of other options, which are derived using the following formulas:

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{8}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} - \frac{P_i}{\min_i P_i} \tag{9}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\left(\lambda \max_i S_i + (1-\lambda)\max_i P_i\right)}; \quad 0 \le \lambda \le 1 \tag{10}$$

Step 9: The final ranking of the alternatives is determined as follows:

$$k_i = (k_{ia}k_{ib}k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{11}$$

4. The Case Study

This paper studies a road section that serves an industrial area located in the city of Misurata, Libya. The road is about 10.4 m wide with a total length of 1300 m. It was constructed a long time ago (more than thirty-five years) and has never been maintained. The heavy trucks often use the route to dump industrial wastes into a nearby landfill. Most of the traffic on the road is classified as heavy traffic. The evaluation was based on a traditional visual inspection of defects that appear in the pavement surface.

Two professional engineers collected detailed information on distresses. Defects data were obtained manually according to the distress identification manual for the long-term pavement performance program (LTPP). Table 1 contains the defects data on pavement surfaces and their severity levels. The pavement condition assessment was carried out and the eight types found are Fatigue cracking, Longitudinal cracking, Transverse cracking, Patches, Potholes, Polished aggregate, and Depression.

Table 1. Pavement distress assessment

No	**Distress Type**	**Severity level**		
		L	M	H
1	Fatigue Cracking (m^2)	977	91	1125
2	Block Cracking	0	0	0
3	Edge Cracking	0	0	0
4	Longitudinal Cracking (m)	9	24	60
5	Reflection Cracking	0	0	0
6	Transverse Cracking (m)	466	1272	3712
7	Patch/Patch Deterioration (m^2)	0.3	10	118
8	Potholes (m^2)	4.55	6.35	23
9	Rutting	0	0	0
10	Shoving	0	0	0
11	Bleeding	0	0	0
12	Polished Aggregate (m^2)	0	2515	773
13	Ravelling	0	0	0
14	Lane-to-Shoulder Drop-off	0	0	0
15	Water Bleeding and Pumping	0	0	0
16	Depression	0	78	138

Low

Medium

High

Figure 2. Severity level of damaged pavement sections

After completing the full survey of visible defects, the data collected shows that the pavement condition of 86 sections varies and is divided into three main levels. One fifth of the total road area suffers from minor or moderate defects such as low-intensity transverse cracks or polished aggregate as shown in Figure 2. The rest of the area, on the other hand, is severely damaged and faces fatigue cracks and depression in the paving layers, in addition to polished aggregate and high-intensity transverse cracks as shown in Figure 2.

In this section, the same defects described above are evaluated. Four experts were invited to participate in determining the importance of each of these criteria (defects). Each expert was interviewed with the aim of clarifying the goal of the research as well as its methodology. Table 2 shows the evaluation criteria and their type.

Table 2. Criteria used

No	Criteria	Type
C1	Fatigue Cracking	Cost
C2	Block Cracking	Cost
C3	Edge Cracking	Cost
C4	Longitudinal Cracking	Cost
C5	Reflection Cracking	Cost
C6	Transverse Cracking	Cost
C7	Patch/Patch Deterioration	Cost
C8	Potholes	Cost
C9	Rutting	Cost
C10	Shoving	Cost
C11	Bleeding	Cost
C12	Polished Aggregate	Cost
C13	Ravelling	Cost
C14	Lane-to-Shoulder Dropoff	Cost
C15	Water Bleeding and Pumping	Cost
C16	Depression	Cost

Linguistic variables can be expressed in grey numbers on a scale shown in Table 3. The case study was also assessed using the grey metrics shown in Table 4.

Table 5 shows the experts' evaluation of each of the criteria (defects) utilized in the study. It also shows the conversion of the linguistic variables into numerical weights, in addition to the whitening degree calculation. The result shows that error 1 is the most important with a weight of 0.05, followed by error 3 with a weight of 0.04 and then error 5 with a weight of 0.03.

Table 3. The importance of grey number for the weights of the criteria

Importance	**Abbreviation**	**Scale of grey number** $\otimes W$
Very Low	VL	[0.0, 0.1]
Low	L	[0.1, 0.3]
Medium Low	ML	[0.3, 0.4]
Medium	M	[0.4, 0.5]
Medium High	MH	[0.5, 0.6]
High	H	[0.6, 0.8]
Very High	VH	[0.8, 1.0]

Table 4. Linguistic assessment and the associated grey values

Performance	**Abbreviation**	**Scale of grey number** $\otimes W$
Very Poor	VP	[0.0, 1.0]
Poor	P	[1.0, 2.0]
Medium Poor	MP	[2.0, 4.0]
Fair	F	[4.0, 5.0]
Medium Good	MG	[5.0, 6.0]
Good	G	[6.0, 8.0]
Very Good	VG	[8.0, 10.]

Table 5. The linguistic assessment of the attributes by experts

C_i	**Expert #1**	**Expert #2**	**Expert #3**	**Expert #4**	$\otimes W$		**Whitening degree**
C_1	VH	VH	VH	L	0.63	0.83	0.7250
C_2	M	H	VH	L	0.48	0.65	0.5625
C_3	ML	M	VH	L	0.40	0.55	0.4750
C_4	M	M	M	L	0.33	0.45	0.3875
C_5	ML	MH	MH	L	0.35	0.48	0.4125
C_6	M	M	M	L	0.33	0.45	0.3875
C_7	MH	M	L	ML	0.33	0.45	0.3875
C_8	H	MH	MH	M	0.50	0.63	0.5625
C_9	H	VH	VH	VH	0.75	0.95	0.8500
C_{10}	MH	MH	VH	MH	0.58	0.70	0.6375
C_{11}	M	VL	VL	VL	0.10	0.20	0.1500
C_{12}	L	M	M	ML	0.30	0.43	0.3625
C_{13}	ML	L	L	ML	0.20	0.35	0.2750
C_{14}	M	L	L	L	0.18	0.35	0.2625
C_{15}	MH	M	M	L	0.35	0.48	0.4125
C_{16}	H	VH	H	VH	0.70	0.90	0.80

The linguistic assessment of each site by experts is shown in Table 6. Transform the linguistic variables into grey numbers according to scales of grey numbers, as shown in Table 3 and Eq. (3). By the assessment of the consequences, grey decision matrix D is calculated.

Table 6. Experts views on suggested technique selection criteria

C_j	Sites	**Expert #1**	**Expert #2**	**Expert #3**	**Expert #4**	$\otimes G_{ij}$
C_1	Unsatisfactory	G	VG	G	VG	[7.009.00]
	Degraded	VP	VP	MP	VP	[0.501.75]
	Adequate	VP	VP	VP	VP	[0.001.00]
C_2	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_3	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_4	Unsatisfactory	P	VP	P	VP	[0.50 1.50]
	Degraded	MG	VG	G	VG	[6.75 8.50]
	Adequate	VP	VP	VP	VP	[0.00 1.00]
C_5	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]

	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_6	Unsatisfactory	VG	G	VG	G	[7.00 9.00]
	Degraded	VP	MG	P	MP	[2.00 3.25]
	Adequate	VP	VP	VP	VP	[0.00 1.00]
C_7	Unsatisfactory	P	VP	VP	VP	[0.25 1.25]
	Degraded	MG	F	P	MG	[3.75 4.75]
	Adequate	VP	G	G	MG	[4.24 5.75]
C_8	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	MP	MP	F	MG	[3.25 4.75]
	Adequate	F	MG	MG	MG	[4.75 5.75]
C_9	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{10}	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{11}	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{12}	Unsatisfactory	MG	VG	VG	VG	[7.25 9.00]
	Degraded	MP	VP	P	VP	[0.75 2.00]
	Adequate	VP	VP	VP	VP	[0.00 1.00]
C_{13}	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{14}	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{15}	Unsatisfactory	VP	VP	VP	VP	[0.00 1.00]
	Degraded	VP	VP	VP	VP	[0.00 1.00]
	Adequate	VG	VG	VG	VG	[8.00 10.0]
C_{16}	Unsatisfactory	F	G	G	MG	[5.25 6.75]
	Degraded	MP	F	MP	MG	[3.25 4.75]
	Adequate	VP	VP	VP	VP	[0.00 1.00]

5. Results

PCI of any pavement section is determined according to ASTM D6433 by calculating the average PCI of all sample units within the inspected section. This is typically created for routine management purposes which allow for early detection of major rehabilitation needs [24]. The average PCI value for the 86 pavement sections considered in this study using the procedure from ASTM D6433 was 31%. The PCI rating indicates unsatisfactory condition of the pavement.

Table 7. Normalised decision-making matrix

	Unsatisfactory	Degraded	Adequate	Weight
C1	0	0.0001	0.4125	0.725
C2	0.325	0.325	0	0.5625
C3	0.275	0.275	0	0.475
C4	0.0001	0	0.225	0.3875
C5	0.2375	0.2375	0	0.4125
C6	0	0	0.225	0.3875
C7	0.2575	0.0236	0.0236	0.3875
C8	0.3125	0	0	0.5625
C9	0.475	0.475	0	0.85
C10	0.35	0.35	0	0.6375
C11	0.1	0.1	0	0.15
C12	0	0	0.2125	0.3625
C13	0.175	0.175	0	0.275
C14	0.175	0.175	0	0.2625
C15	0.2375	0.2375	0	0.4125
C16	0	0	0.45	0.8

Table 8. Weighted normalised decision-making matrix

	Unsatisfactory	Degraded	Adequate
C1	0	0	0.299
C2	0.183	0.183	0
C3	0.131	0.131	0
C4	0	0	0.087
C5	0.098	0.098	0
C6	0	0	0.087
C7	0.1	0.009	0.009
C8	0.176	0	0
C9	0.404	0.404	0
C10	0.223	0.223	0
C11	0.015	0.015	0
C12	0	0	0.077
C13	0.048	0.048	0
C14	0.046	0.046	0
C15	0.098	0.098	0
C16	0	0	0.36

Table 9. Relative weights of the alternatives for different aggregation strategies

	P_i	S_i+P_i	k_{ia}	k_{ib}	k_{ic}	k_i	rank
Unsatisfactory	6.321	7.842	0.426	3.774	1.000	2.905	1
Degraded	5.417	6.671	0.362	3.182	0.851	2.458	2
Adequate	2.981	3.900	0.212	2.000	0.497	1.498	3

The next step is to form normalised decision-making matrix, which shown in Table 7. Table 8 shows the weighted normalised decision-making matrix. The weights obtained by using grey theory are used.

Table 9 shows the relative weights of the alternatives using different aggregation strategies. The results show that the road is in unsatisfactory condition.

6. Discussion

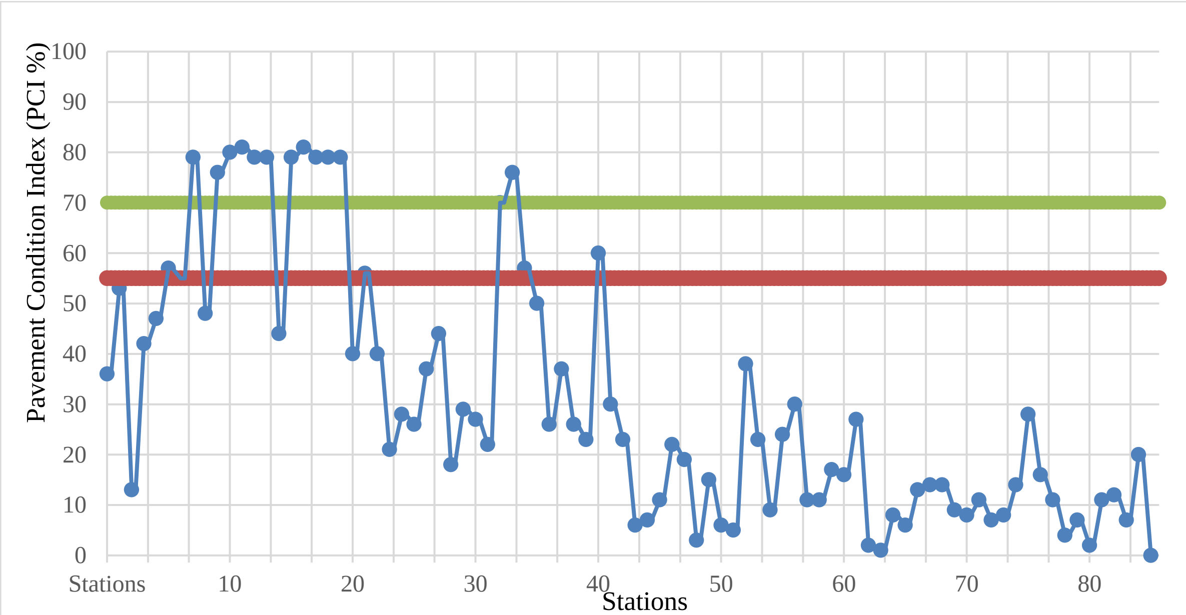

Figure 3. Case study PCI values as per ASTM 6433 procedure

Based on the results, similar evaluation conclusions were obtained by comparing the two methods. Distress estimation on both models has given comparable evaluation outcomes. However, both pavement performance assessments are identical, where the road surface is obviously damaged and deteriorated and urgent maintenance is required very soon. 80% of the total road area suffers from highly defected pavements. Figure 3 shows the pavement condition along the road, where PCI values fall below 55 for most roadway sections. The results also show that rutting, depression, and fatigue cracking are ranked sequentially as the most important aspects. These defects have a direct influence on the safety of people and the targeted level of service. On the other hand, Marcelino et al. [26] evaluated pavement condition based on functional and structural aspects. Functional criteria include traffic and safety, while structural criteria include pavement condition and social equity. Moreover, Pescador Junior et al. [27] estimated pavement condition objectively and subjectively.

To ensure the applicability and the accuracy of the MCDM model in the evaluation process of pavement performance, a statistical analysis was carried out using the t-test paired two-sample method assuming unequal variances. The results indicated that there is no significant difference between values as shown in Table 10. Therefore, the MCDM model is a reliable method that could be used in the field of pavement performance evaluation. Similarly, Pescador et al. [27] concluded that the results on both methods are almost identical. In addition, Marcelino et al. [26] study demonstrated that MCDM methods are suitable and useful. However, the application of the model is limited to the existence of experience, and adequate data that are coherently related to the precision of the results. Although pavement evaluation methods are widely used, a well-trained assessment team is demanded to evaluate the roadway pavement condition, and provide enough information on road defects. Thus, the models' accuracy is limited to the experience and skills of the surveyors and the sufficiency of data.

Table 10. t-Test: Two-Sample assuming unequal variances

	MCDM	*PCI*
Mean	0.077	237.5458
Variance	0.01216	470228.2
Observations	48	48
Hypothesized Mean Difference	0	
df	47	
t Stat	-2.39924	
P(T<=t) one-tail	0.010224	
t Critical one-tail	1.677927	
P(T<=t) two-tail	0.020447	
t Critical two-tail	2.011741	

7. Conclusion

It is very important to inspect the road surface as it will be damaged over its service life due to weather factors and heavy traffic. This inspection helps identify the types of damage and, therefore, the maintenance methods that can ensure that the road remains in good condition and serviceable for the longest possible time. As an essential first step in an effective maintenance management system, an initial assessment is conducted to identify the most significant road defects. This helps decision-makers make appropriate decisions regarding future maintenance operations.

In this study, PCI was obtained both objectively and subjectively. It should be mentioned that there was no significant difference between the values obtained by the two methods. As a matter of fact, the t-test was used to compare the results obtained, and the result showed that there was no significant difference between the results obtained by the two methods. This indicates the possibility of using subjective methods for an initial assessment of the condition of the roads and an appropriate decision on their maintenance. In addition, this work identified the areas with the highest frequency of defects. The results showed that 80% of the road studied suffers from major defects and requires maintenance. This study approach can be extended for future studies by comparing objective and subjective results on different topics that require a decision-making. Future research should aim to replicate results of MCDM with other pavement performance measures.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of Interest

The authors declare that they have no conflicts of interest.

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