Using an Integrated Multi-criteria Decision-Making Based Approach for Road Condition Assessment

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Abstract—**Road networks are the backbone of transportation infrastructure systems around the world. Thus, it is crucial to maintain the integrity of road networks to facilitate economic and social prosperity. Proper assessment of road pavement conditions is essential to effectively preserve road networks in good condition. The development of adequate condition indices or ranking techniques to evaluate road pavement sections necessitates driving reliable weights for the various road pavement condition criteria. Different objective and subjective weighting approaches are available in the literature. Objective approaches are criticized for failing to adequately consider the varying significance of different criteria, whereas subjective approaches are prone to bias and uncertainty. Hence, this research aims at developing weights by integrating the application of the Analytical Hierarchy Process (AHP), Inter-criteria Correlation (CRITIC), and Monte-Carlo simulation to develop reliable weights for three condition criteria of cracking, rutting, and the International Roughness Index (IRI). Then, Multi-Attribute Utility Theory (MAUT) is applied to develop a Road Pavement Condition Rating (RCR). Also, six other multi-criteria decision-making techniques (MCDM) are used to rank the road pavement sections according to their condition. The developed techniques are used to assess more than 300 road pavement sections. The comparison between the ranking results of the different MCDM techniques indicates that they are highly correlated.**

***Keywords*—pavement condition assessment, Multi-criteria Decision-making (MCDM), Analytical Hierarchy Process (AHP), Multi-Attribute Utility Theory (MAUT), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Combined Compromise Solution (CoCoSo)**

I. INTRODUCTION

Road networks are the backbone of the transportation infrastructure all over the world. They are critical for facilitating the movement of ever-increasing numbers of humans and goods [1]. However, keeping road pavement in good condition is increasingly challenging. According to ASCE's 2021 Report Card for America's Infra-structure, 41.9% of roads in the USA are in poor or mediocre condition [1]. The challenge of maintaining roads in good condition boils down to three aspects, the massive size of the road networks, the progressive deterioration of road pavements, as well as the tightened budget constraints [2]. Considering the current size of road networks, some agencies have started shifting their priorities from constructing new road pavement to maintaining the existing assets [3, 4].

Different highway agencies evaluate road pavement conditions using various condition indices. Condition indices are used to provide a measurable assessment of the current road pavement condition. Subsequently, they constitute reliable tools to rank and prioritize treatment activities objectively. Highway agencies regularly collect distress and performance measures data such as roughness, rutting, cracking, patching, and raveling to evaluate the condition of their road pavement networks [5]. Quantitative-based and composite condition indices can provide a more representative evaluation of the overall road pavement condition. However, agencies face troublesome challenges when adopting them. One critical challenge is that quantitative-based condition indices are usually data demanding, e.g., PCI for asphalt pavement requires data on 19 different destresses. In some instances, lack of data on some distresses and condition criteria renders using some traditional indices impractical. Another problem is the uncertainty regarding the criticality of different condition criteria composing the condition index.

Numerous efforts have been devoted to developing condition assessment models for road pavement. Various agencies use different approaches to assess their road pavement condition. However, the weighted average of individual condition criteria (e.g., roughness index, rutting index, cracking index, and structural index) is a widely used approach [6]. Weights of the various condition criteria are usually derived subjectively using expert judgment. For example, Oklahoma DOT uses the Pavement Quality Index (PQI), which employs the weighted summation of multiple condition criteria.

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Oklahoma DOT PQI is calculated as the weighted sum of 40% ride index, 30% rut index, 15% structural cracking index, and 15% functional cracking index. North Carolina, on the other hand, calculates the Overall Condition Index (OCI) by subtracting points based on the severity and extent of main distresses, such as transverse cracking, alligator cracking, ride, rutting, and patching [7]. Iowa DOT uses different combinations of rutting, crack, faulting, ride quality, and friction based on pavement material to calculate the Pavement Condition Index (PCI). However, Iowa's calculation of PCI is based on old statistical regression equations. In a bid to improve and simplify the PCI calculation, Jia [8] proposed a modified condition rating system for the State of Iowa. The Proposed system has a 100-point scale to combine the individual indexes using a simple weighted sum of 40% ride index, 40% cracking index, and 20% rutting [8].

Thus, it is essential to develop reliable evaluation techniques considering data availability and the involved uncertainty and bias in the usually used subjective weighting techniques. Combining the application of the objective weighting approaches, subjective weighting approaches, and the Monte-Carlo simulation can provide a more reliable methodology for developing reliable weights. Thus, this study aims at developing combined condition criteria weights using Analytical Hierarchy Process (AHP), Inter-criteria Correlation (CRITIC), and Monte Carlo simulation. Also, the large corpus of literature on MCDM techniques paves the way to establish more sophisticated tools to evaluate and rank road pavement sections according to their condition. Thus, this study aims at utilizing different multi-criteria decision-making techniques (MCDM) techniques to assess the road pavement based on International Roughness Index (IRI), cracking, and rutting. Seven MCDM techniques of MAUT, TOPSIS, COCOSO, WASPAS, OCRA, GRA, and COPRAS are used to rank road pavement sections according to their condition. Also, Multi-Attribute Utility Theory (MAUT) was used to advise the development of a new pavement condition index of Road Pavement Condition Rating (RCR).

II. METHODOLOGY

The present research study intends to develop a new methodology for evaluating and ranking road pavement sections. The new assessment approach constitutes two stages. The first stage involves developing integrated objective-subjective weights for the condition criteria. The second stage entails applying and comparing several MCDM techniques to rank road pavement sections. The methodology of the present research study is depicted in Fig. 1. As shown in Fig. 1, first, the condition criteria are selected. Second, three types of data are obtained: pavement inspection data (IRI, cracking, and rutting), expert judgment on the criticality of the individual condition criteria, as well as road pavement utility values at different severity levels of the various condition criteria. Third, weights are derived by integrating the application of AHP, CRITIC, and Monte Carlo simulation. Forth, seven MCDM techniques are employed to rank the different road pavement sections according to their condition. Also, MAUT is further used to establish a new pavement condition index called RCR. Finally, the results of the different MCDM techniques are compared.

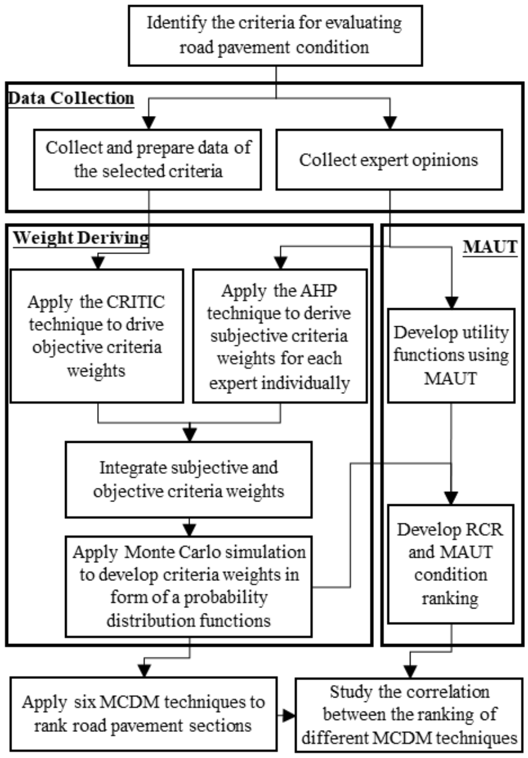


Fig. 1. Framework of the developed road condition assessment model.

A. Condition Criteria Selection

The combination of roughness and a selection of other distresses (especially cracking and rutting) is the most common in road pavement condition assessments [6]. In this regard, two main factors can be noted. First, IRI, rutting, and cracking are among the most representative indicator of road pavement condition. Second, many highway agencies regularly collect inspection data of IRI, rutting, and cracking. In the USA, the Moving Ahead for Progress in the 21st Century Act (MAP-21) requires all agencies to acquire three types of data (IRI, rutting, and cracking) about asphalt pavements condition [9]. Some agencies have already started adopting the collected data in their decision-making process. However, developing an overall index considering the three types of data is still short in progress. Thus, IRI, rutting, and cracking are chosen for evaluating road pavement in the present research.

B. Data Collection

Data are firstly collected by Tabara [10] for the three adopted condition criteria of IRI, cracking, and rutting. The data are gathered for 302 road pavement sections managed by the Nebraska Department of Roads (NDOR). Statistics of the collected data are presented in Table I. Values of the IRI in the collected data range from zero to about 6.7 mm/m. Crack width ranges between zero and about 65 mm, whereas rut depth varies between 0 and 19 mm. Average values of IRI, cracking, and rutting are 2.9 mm/m, 11.8 mm, and 4.4 mm, respectively.

Expert opinions are then collected via ten questionnaires to evaluate the subjective weights of the three criteria. Experts are asked to provide a pairwise comparison based on the Saati nine-point scale [11].

TABLE I. STATISTIC OF THE COLLECTED DATA ON IRI, CRACKING, AND RUTTING

Statistic measure	Condition criteria		
	IRI (mm/m)	Cracking (mm)	Rutting (mm)
Minimum	0	0	0
Maximum	6.7	65.3	19.0
Average	2.9	11.8	4.4

The collected data are later used to derive criteria weights by applying the AHP technique. Also, data are collected to assess their impact on the road pavement condition at various severity levels. The collected data of utility assessment at different severity levels are then used to develop utility functions for the three criteria considered in this study. The obtained utility functions are used to calculate the utility values of the different road pavement sections using MAUT.

C. Weight Deriving

AHP, CRITIC, and Monte Carlo simulation are employed to develop integrated subjective-objective weights in the form of probability distribution functions. AHP is utilized to scrutinize the relative importance weights of the aforementioned criteria. The AHP technique is a useful tool for studying complex multi-dimensional optimization problems [11]. It was developed by Saaty in the 1970s to account for qualitative data analysis [11]. It utilizes a pairwise comparison matrix to compare alternatives on a ratio scale without considering the interdependencies between different factors [12]. The hierarchy structure can be divided into three sections: the ultimate goal of the problem, all viable solutions, known as alternatives, and the criteria used to evaluate the alternatives [13]. Depending on the intricacy of the problem, the criteria are divided into sub-criteria, sub-sub-criteria, and so forth. Subsequently, a pairwise comparison is conducted on the criteria at the same level to evaluate any two elements in the hierarchy. The pairwise comparison is carried out with respect to the overall goal based on experts' judgment. The pairwise comparison is conducted on a nine-point scale where one is assigned if the elements are equally important, and nine is given if the element is absolutely more important [11]. Based on the pairwise comparison of each two elements, a positive reciprocal matrix $A = (a_{ij})$ is generated such that $a_{ii} = 1$ and $a_{ij} = 1/a_{ji}$ as shown in Eq. (1).

$$A = \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ 1/a_{1n} & \cdots & 1 \end{bmatrix} \tag{1}$$

where n is the number of elements being compared per one set of pairwise comparisons; a_{ij} = importance of alternative i over alternative j; and a_{ji} = importance of alternative j over alternative i.

The Preference assessments obtained from each pairwise comparison in matrix A are transferred into a priority vector w. In most cases, the eigenvector method is preferable to derive the priority vector from the reciprocal matrix. The eigenvector approach computes Wh as the primary eigenvector corresponding to the biggest eigenvalue in matrix A, referred to as the principal eigenvalue λ_{max}, as shown in Eq. (2).

$$Aw' = \lambda_{\max} w' \tag{2}$$

where λ_{max} is the principal eigenvalue $\geq n$; and $Wh' = [Wh_1, Wh_2, \ldots, Wh_n]^T$.

When performing pairwise comparisons, it is critical to verify the consistency property by computing the Consistency Index (CI). Subsequently, the Consistency Ratio (CR) is calculated to verify the judgments' reliability.

Moreover, the CRITIC technique is used to derive unbiased criteria weights without considering expert inputs [14]. Criteria weights are evaluated based on the standard deviation of the data and the relationship between different condition criteria. The normalized weight (Wc_i) of the i_{th} criterion is evaluated using equation Eq. (3).

$$Wc_i = \frac{Cr_i}{\sum_{j=1}^{n} Cr_j} \tag{3}$$

where Cr_i is calculated for i_{th} criterion as shown in Eq. (4).

$$Cr_i = \sigma_j \sum_{j=1}^{m} (1 - c_{j,i}) \tag{4}$$

where σ_j is the standard deviation of the normalized values of the criterion Cr_i; and C_{ji} is the correlation coefficient between the criterion i and j.

Aftermath, criteria weights derived using the CRITIC technique are integrated with that calculated using the AHP based on the judgment of each expert individually. The integrated weights $W_{i,j}$ are calculated by multiplying the CRITIC weight Wc_i and AHP weight $Wh_{i,j}$ as shown in Eq. (5). Then, the normalized weight $Wn_{i,j}$ for i_{th} criterion and considering the judgment of the j_{th} expert is derived.

$$W_{i,j} = Wc_i \times Wa_{i,j} \tag{5}$$

where $W_{i,j}$ is the integrated weight for the i_{th} criterion and considering the judgment of the j_{th} expert.

Then, Monte Carlo simulation is employed to account for the uncertainties and subjectivity associated with experts' judgments. Monte Carlo simulation has been utilized in developing various pavement deterioration and condition assessment models without demanding an extensive historical database. Rodríguez *et al*. [15] used the Monte Carlo simulation model to develop a probabilistic model that predicts the roughness of asphalt pavement considering all the input variables in random form. However, the stochasticity of different distresses and performance measures weights has rarely been included in pavement condition assessments.

Hence, the integrated normalized weights Wn of the condition criteria are analyzed using @Risk software. Three goodness-of-fit tests are used to find the best-fit distribution of the condition criteria weights. These tests are Ch-squared, Kolmogorov Smirnov, and Anderson Darling. Thus, Probability distribution functions (PDF) are ultimately derived for the different condition criteria weights.

D. Application of MCDM Techniques

Seven MCDM techniques are used to evaluate the condition of road pavement sections. Six MCDM techniques of TOPSIS [16], COCOSO [17], WASPAS [18], OCRA [19], GRA [20], and COPRAS [21] are used to rank road pavement sections according to their condition. Due to size limitations, the specifics of the utilized MCDM techniques are not elaborated. However, the details of their application can be found in the relevant material [16–21]. Monte Carlo simulation is run numerous times (1000 times) according to the obtained best-fit distribution across each condition criteria. The average values are used as criteria weight input for the six utilized MCDM techniques. It is important to note that the aforementioned MCDM techniques help rank road pavement sections according to their condition. Thus, they are particularly useful for agencies that adopt the worst-first (W-F) approach in their maintenance programs.

Moreover, the obtained PDF of the criteria weights alongside the utility values are then used to develop the MAUT-based model. Utility functions are a paramount component in MAUT models. The utility functions are modeled on a scale of ten points to evaluate the effect of the various levels of different pavement attributes. On the advised scale, zero represents the worst utility value, whereas ten represents the best. Utility value scores at given attributes' levels are collected from ten respondents. Attribute utility scores assigned by the different respondents are averaged at each attribute level. Then, the averaged utility score values are used to develop the utility functions for the three factors. The MATLAB Curve Fitting toolbox was employed to obtain functions representing the relationship between the attribute levels and utility values. Ultimately, third-order polynomial regression is leveraged to construct the utility functions by compiling the utility scores reported by the experts in the questionnaire responses. The output of this model is a probabilistic distribution for the condition rating of each road section, and the mean of the distribution is used to signify the ultimate condition rating of this section. Also, road sections are ranked accordingly.

E. Correlation of the MCDM Results

To compare the used MCDM techniques, the correlation between the obtained raking of the road pavement sections is performed. As the results are obtained in the form of ranking, the Pearson correlation is not useful. Instead, the Spearman correlation is used to analyze the relationship between the ranking results of the seven MCDM techniques.

III. Results and Analysis

A. Weights

A pairwise comparison matrix was advised individually for the collected ten questionnaire responses. The pairwise comparison matrices were extracted to represent the relationship between the IRI, cracking, and rutting. A sample of the pairwise comparison matrix that constitutes the evaluation of respondent 3 is presented in Table II. As illustrated in Table II, respondent 3 assigned lower importance to the IRI in comparison to cracking and rutting. The comparison shows that cracking is twice as significant as the IRI, whereas rutting is 1.5 more important than the IRI. Also, Respondent 3 prioritized cracking over rutting. Cracking was assigned a relative importance of 1.3 compared to rutting. Aftermath, the relative weights of the three factors are calculated. The calculated weights are presented for the individual respondents in Table III. For example, the weights IRI, cracking, and rutting are calculated as 0.22, 0.44, and 0.33 for respondent three, as shown in Table III.

TABLE II. Pairwise Comparison of Respondent Three

Criteria	IRI	Cracking	Rutting
IRI	1	0.5	0.66667
Cracking	2	1	1.33333
Rutting	1.5	0.75	1

TABLE III. AHP and AHP-CRITIC Based Weights for the Individual Responses

Response	AHP			AHP-CRITIC		
	IRI	Cracking	Rutting	IRI	Cracking	Rutting
1	0.33	0.50	0.17	0.27	0.53	0.20
2	0.33	0.33	0.33	0.26	0.34	0.39
3	0.22	0.44	0.33	0.17	0.45	0.38
4	0.36	0.36	0.27	0.29	0.38	0.33
5	0.13	0.63	0.25	0.10	0.62	0.28
6	0.22	0.44	0.33	0.17	0.45	0.38
7	0.33	0.56	0.11	0.27	0.59	0.14
8	0.42	0.42	0.17	0.34	0.45	0.21
9	0.14	0.57	0.29	0.11	0.57	0.32
10	0.18	0.36	0.45	0.14	0.36	0.51

On the other hand, the collected data for the three condition criteria are used to derive weights using the CRITIC technique. The correlation values c are presented in Table IV. The normalized weights Wc are calculated as 0.263, 0.344, and 0.392 for IRI, cracking, and rutting, respectively. Aftermath, integrated weights W are calculated using Eq. (5). The integrated weights are presented in Table III. For example, the integrated weights for IRI, cracking, and rutting are calculated as 0.17, 0.45, and 0.38 for respondent three, as shown in Table III.

Monte Carlo simulation is subsequently applied to account for the stochasticity in the responses. The calculated weights considering the ten responses are used to advise probability distribution for the three factors using @Risk software. The developed probability distributions and their parameters are presented in Table V. A uniform probability distribution function is developed for IRI with an upper threshold (b) of 0.372 and a lower threshold (a) of 0.067. Also, a uniform probability distribution function is adopted to represent the probability distribution of the cracking with an upper threshold (b) of 0.652 and a lower threshold (a) of 0.313. A normal distribution function is adopted to model the probability distribution of the relative weight of rutting. The developed function has an average (μ) of 0.314 and a standard deviation (σ) of 0.111. The developed PDF are successfully tested against the three checks of Kolmogorov Smirnov, Anderson Darling, and Chi-Squared. The generated probability distributions are used to calculate the condition rating index of the different sections as shown later.

TABLE IV. CORRELATION BETWEEN CONDITION CRITERIA

	IRI	Cracking	Rutting
IRI	1.00	0.24	0.06
Cracking	0.24	1.00	0.18
Rutting	0.06	0.18	1.00

TABLE V. PROBABILITY DISTRIBUTION FUNCTIONS (PDF) FOR CONDITION CRITERIA WEIGHTS

Attribute	PDF	Parameters
IRI	Uniform	a = 0.067, b = 0.372
Cracking	Uniform	a = 0.313, b = 0.652
Rutting	Normal	μ = 0.314, σ = 0.111

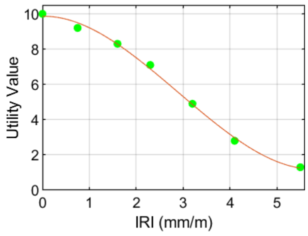
B. MCDM

The use of the attribute utility theory entails the development of utility functions for each condition criterion. Various types of functions are explored before adopting third-order polynomial functions to model the three utility functions for IRI, cracking, and rutting. The graphical representation of the developed utility function is presented in Fig. 2.

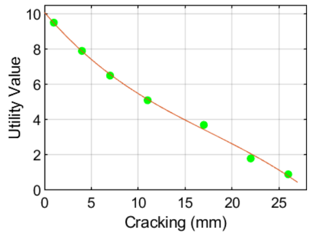
The proposed condition index RCR constitutes a weighted average of the utility scores of the three condition criteria, as presented in Eq 6. As the condition criteria weights are available in the form of PDF, 1000 samples are generated to calculate the RCR of each road pavement section. The RCR values are used to constitute a normal distribution function, as presented in Fig. 2. The condition index RCR is used to assess the condition of the 302 road pavement sections. Samples of the results obtained for road pavement sections 50, 60, and 70 are presented in Fig. 3. Having RCR as a probability distribution function can help decision-makers to consider different confidence levels while setting their treatment plans. However, in current research, the mean value is used to signify the condition of the road pavement sections. Then, road pavement sections are ranked accordingly.

$$RCR = \sum_{i=1}^{m=3} PDF_i \times U_i \quad (6)$$

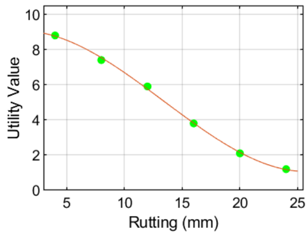
where m is the number of condition criteria; PDF_i and U_i are the PDF and the utility score for the condition criteria i, respectively.



(a) IRI

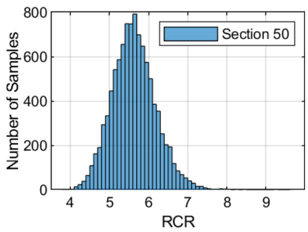


(b) Cracking

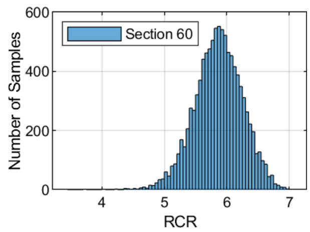


(c) Rutting

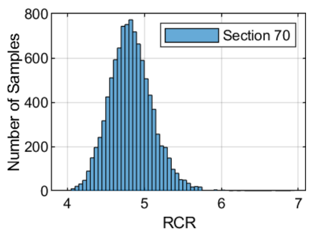
Fig. 2. Utility functions for (a) IRI, (b) Cracking, and (c) Rutting.



(a) Section 50



(b) Section 60



(c) Section 70

Fig. 3. Histograms showing RCR values for sections 50, 60, and 70 using 1000 samples.

The condition of the different road pavement sections is also evaluated using the other six MCDM techniques. A sample of the results is presented in Fig. 4 for the road sections (1–35).

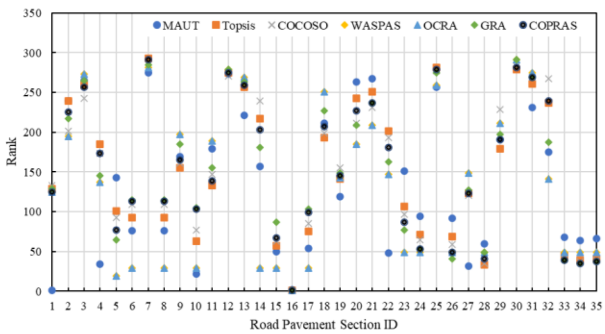


Fig. 4. Sample of the ranking results for the different MCDM techniques.

C. Correlation

The correlation of the seven MCDM techniques results is presented in Table VI. The results indicate a high correlation between the different MCDM techniques. Table VI shows a remarkably high correlation between the results obtained using TOPSIS, COCOSO, OCRA, GRA, and COPRAS. A maximum correlation of 0.99 is observed between CORPAS and GRA, as well as COPRAS and TOPSIS. Table VI indicates that MAUT and WASPAS have relatively lower correlations with other MCDM techniques. The least correlation of 0.83 is found between MAUT and WASPAS.

TABLE VI. CORRELATION MATRIX OF THE RANKING RESULTS FOR THE DIFFERENT MCDM TECHNIQUES

	MAUT	**TOPSIS**	**COCOSO**	**WASPAS**	**OCRA**	**GRA**	**COPRAS**
MAUT	1.00	0.88	0.86	0.83	0.87	0.89	0.87
TOPSIS	0.88	1.00	0.98	0.85	0.94	0.97	0.99
COCOSO	0.86	0.98	1.00	0.85	0.92	0.97	0.98
WASPAS	0.83	0.85	0.85	1.00	0.91	0.91	0.88
OCRA	0.87	0.94	0.92	0.91	1.00	0.97	0.96
GRA	0.89	0.97	0.97	0.91	0.97	1.00	0.99
COPRAS	0.87	0.99	0.98	0.88	0.96	0.99	1.00

IV. CONCLUSIONS

Sustaining road pavement in good condition is a challenging task given budgetary constraints, which necessitate prioritizing the maintenance of some road pavement sections over others. Evaluating road pavement conditions is essential for developing effective maintenance plans. Thus, this study develops an MCDM-based methodology for assessing road pavement conditions based on IRI, cracking, and rutting. The current study integrates the application of multiple MCDM techniques. The AHP, CRITIC, and Monte Carlo simulation techniques are used to develop criteria weights as PDF. Considering the obtained weights, cracking has the highest impact on the overall road pavement condition, whereas IRI has the least. Seven MCDM techniques of MAUT, TOPSIS, COCOSO, WASPAS, OCRA, GRA, and COPRAS are used to rank road pavement sections. Also, MAUT is used to derive a new condition index called RCR. The MCDM techniques are applied to assess 302 road sections managed by the NDOR. The obtained results show a high correlation between the different MCDM techniques, particularly between TOPSIS, COCOSO, OCRA, GRA, and COPRAS. Future research is needed to compare the results of the developed approaches with existing standard indices.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ali Fares, Eslam Mohammed Abdelkader, Nour Faris analyzed the data; Ali Fares wrote the paper; Eslam, Eslam Mohammed Abdelkader, Nour Faris revised and edited the paper; Tarek Zayed supervised the research; all authors had approved the final version.

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