

Research Article

The Quality Assessment of Pavement Performance Using the Entropy Weight-Variable Fuzzy Sets Model

Y. Li,¹ Y. H. Wang,² Q. H. Wu ^(b),¹ and X. B. Gu ^(b)

¹School of Architecture and Civil Engineering, Chengdu University, Chengdu, Sichuan, China
 ²School of Civil Engineering, Sichuan University of Science & Engineering, Zigong, China
 ³School of Civil Engineering, Nanyang Institute of Technology, Nanyang, Henan, China

Correspondence should be addressed to Q. H. Wu; 15700679755@139.com

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As the assessment of pavement performance has considerable repercussions for the construction quality of roads, the study of the assessment procedure used is extremely critical. Riding quality index (RQI), pavement condition index (PCI), pavement structure strength index (PSSI), skid resistance index (SRI), and antirutting index (ARI) are selected as the assessment indexes of pavement performance. Then, the entropy weight-variable fuzzy sets model is introduced. Second, a relative membership degree matrix for the variable fuzzy sets is established, and the entropy weight method is used to determine the weight coefficients considering the uncertainty in the assessment indices. Finally, the quality level of pavement performance is determined by using the mean ranking feature value. The conclusions demonstrate a very accurate rate for the quality assessment of the pavement performance based on the variable fuzzy sets model compared to that based on the current specification, and the proposed method is feasible for the quality assessment of pavement performance, thus providing a novel means of assessing the quality level of pavement performance in the future.

1. Introduction

Increasing traffic flow has exacerbated highway pavement deterioration, resulting in significant losses for the national economy [1]. To improve the regulation and maintenance of highways, it is vital to correctly assess the pavement performance quality of highways.

Researchers have developed many methods to assess the quality level of pavement performance [2]. For example, the system analysis evaluation method [3], the comprehensive evaluation method [4], the extension cloud evaluation method [5], the extension evaluation method [6], the fuzzy compound matter element method [7], the gray fuzzy clustering method [8], the regression analysis method [9], the multivariate statistical techniques [10], the wavelet technique [11], and evaluation method using analytical connection coefficients [12]. These methods have furthered the development of assessment systems but still exhibited some shortcomings [13]. For example, the comprehensive

evaluation index is obtained from the weights of the pavement performance index and thus requires repartitioning the class standard of the synthetic assessment index [14]. The extension theory and cloud models can be used to address the randomness and fuzziness of level threshold values [15] but involve a complex calculation process that limits its development and application. The fuzzy mathematical method can easily distinguish the difference between the adjacent levels. The assessment using these methods can be either qualitative or qualitative, involving many humans. Thus, the assessment results have limited the objectivity.

To overcome the shortcomings of the above-mentioned methods, the variable fuzzy set theory is applied to assess the pavement performance. The concept of fuzzy logic is defined as the description of imprecision or vagueness, which gives fuzziness a scientific description and generates great significance. So, the entropy weight-variable fuzzy sets are introduced in this study to assess the quality level of pavement performance by accounting for imprecise, vague, and fuzzy information in decision-making [16, 17]. For example, Gu et al. [18] analyze the risk level of landslide hazards in Shiwangmiao, Chongqing using the intuitionistic fuzzy sets-TOPSIS model, and the selection of a route for the transport of hazardous materials using a fuzzy logic system is performed by Milosevic et al. [19]. This method offers advantages, such as a precise algorithm and practical operability, and is effectively applied to the grading standards in interval form rather than a point value. Thus, it represents a considerable improvement relative to the traditional fuzzy sets model, the model can accurately convey the risk degree of pavement performance, so it has higher accuracy. To reveal the advantage of the proposed model, Lanwu Highway is applied to assess the quality level of pavement performance.

The study is organized as follows: in Section 2, the entropy weight-variable fuzzy sets theory is introduced at first; in Section 3, the riding quality index (RQI), pavement condition index (PCI), pavement structure strength index (PSSI), skid resistance index (SRI), and antirutting index (ARI) are selected as the assessment indexes, an assessment model for the level quality of the pavement performance is established, and the corresponding assessment results are analyzed; discussions and comparative analysis are performed in Section 4. Conclusions and future scope are analyzed in Section 5.

2. Methodology

2.1. The Principle of Variable Fuzzy Sets. Assuming that U is a fuzzy concept and the elements F and F^c are the basic fuzzy attributes that are antithetical. $\mu_F(u)$ and $\mu_{F^c}(u)$ are the corresponding membership degrees that satisfy with $\mu_F(u) + \mu_{F^c}(u) = 1$, $0 \le \mu_F(u) \le 1$ and $0 \le \mu_{F^c}(u) \le 1$. The relative difference degree [20] of u to F is defined as $D(u) = \mu_F(u) - \mu_{F^c}(u)$.

In the mapping $D_F: D \longrightarrow [-1, 1], u \longrightarrow D_F(u) \in [-1, 1], u$ denotes the relative difference function of *F*.

According to the definition of the complementary set for the fuzzy sets,

$$D_F(u) = 2\mu_F(u) - 1 \text{ OR } \mu_F(u) = \frac{(1 + D_F(u))}{2}.$$
 (1)

Let

$$V = \left\{ \frac{(u, D)}{u \in U, D_F(u) = \mu_F(u) - \mu_{F^c}, D \in [-1, 1]} \right\},$$

$$F_+ = \{u | u \in U, 0 < D_F(u) \le 1\},$$

$$F_- = \{u | u \in U, -1 < D_F(u) \le 0\},$$

$$F_0 = \{u | u \in U, D_F(u) = 0\}.$$

(2)

Here, V denotes the fuzzy variable sets and F_+ , F_- , and F_0 denote an attracting set, a repelling set, and a balance boundary, respectively.



FIGURE 1: Schematic of the position relation.

2.2. Determination of the Relative Membership Degree of *Indexes*. To assess the pavement performance, it is assumed that a sample set can be established as follows:

$$X = (x_{ij}), \tag{3}$$

where x_{ij} denotes the eigenvalue of the index *i* of sample *j*, *i* = 1, 2, ..., *m*; *j* = 1, 2, ..., *c*. c denotes the level of the index, such that as the magnitude of c increases, the level becomes more inferior; the attractive range I_{ab} can be obtained as follows:

$$I_{\rm ab} = \left(\left| a_{ij}, b_{ij} \right| \right). \tag{4}$$

Enlarging I_{de} based on the upper and lower bounds of the adjacent intervals yields the following expression:

$$I_{de} = \left(\left| d_{ij}, e_{ij} \right| \right). \tag{5}$$

According to the physical meaning of the assessment index, the class standard of the index can be determined by the matrix F, which is expressed as follows:

$$F = \begin{bmatrix} F_{11} & \dots & F_{1j} \\ \dots & \dots & \dots \\ F_{i1} & \dots & F_{ij} \end{bmatrix}.$$
 (6)

The parameter F_{ij} can be expressed in terms of a_{ij} and b_{ij} as follows:

$$F_{ij} = \frac{c-j}{c-1}a_{ij} + \frac{j-1}{c-1}b_{ij},$$
(7)

where for j = 1, $F_{i1} = a_{i1}$; for j = c, $F_{ic} = b_{ic}$; for j = (c + 1/2), $F_{ij} = (a_{ij} + b_{ij}/2)$.

It is assumed that $X_0(a, b)$ is the attractive range of the fuzzy variable sets V, namely, $0 \le D_F(u) \le 1$, and X = [d, e] is included in the upper and lower range intervals of $X_0(X_0 \subset X)$, as shown in Figure 1.

F is the point value of $D_F(u) = 1$ in the attractive range [a, b]; a physical analysis shows that when *x* is located to the left of point *F*, its relative difference function model can be expressed as follows:

$$\begin{cases} D_F(u) = \left(\frac{x-a}{F-a}\right)^{\beta}; x \in [a, F], \\ D_F(u) = -\left(\frac{x-a}{d-a}\right)^{\beta}; x \in [d, a]. \end{cases}$$
(8)

When x is located to the right of point F, its relative difference function model can be expressed as follows [17]:

$$\begin{cases} D_F(u) = \left(\frac{x-b}{F-b}\right)^{\beta}; x \in [F,b], \\ D_F(u) = -\left(\frac{x-b}{e-b}\right)^{\beta}; x \in [b,e], \end{cases}$$
(9)

where β is a non-negative number, for $\beta = 1$ in equations (7) and (8), the relative difference function model is a linear function, constrained by the following 3 conditions: (1) for $x = a, x = b, D_F(u) = 0$; (2) for $x = F, D_F(u) = 1$; (3) for $x = d, x = e, D_F(u) = -1$.

Equations (7) and (8) can be substituted into equation (1) to yield the relative membership degree, as shown in the following equation:

$$\begin{cases} \mu_{F}(u) = 0.5 \left[1 + \left(\frac{x-a}{F-a}\right)^{\beta} \right]; x \in [a, F], \\ \mu_{F}(u) = 0.5 \left[1 - \left(\frac{x-a}{e-a}\right)^{\beta} \right]; x \in [e, a]. \end{cases}$$

$$\begin{cases} \mu_{F}(u) = 0.5 \left[1 + \left(\frac{x-b}{F-b}\right)^{\beta} \right]; x \in [F, b], \\ \mu_{F}(u) = 0.5 \left[1 - \left(\frac{x-b}{e-b}\right)^{\beta} \right]; x \in [b, e]. \end{cases}$$
(10)
(11)

2.3. The Determination of Index Weights. The entropy weighting method is used to determine the index weights. This method consists of calculating the weight of each index [21] by using the magnitude of the entropy. The calculation procedure is detailed as follows:

Assuming that there are *m* cases of debris flow and *n* assessment indexes, so the original matrix can be expressed as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}.$$
 (12)

(2) The main indexes X_{ij} are normalized. The positive indicator is calculated as follows:

$$x_{ij}' = \frac{x_{ij} - \min\{x_{ij}, \dots, x_{nj}\}}{\max\{x_{1j}, \dots, x_{nj}\} - \min\{x_{ij}, \dots, x_{nj}\}}.$$
 (13)

The negative indicator is calculated as follows:

$$x_{ij}' = \frac{\min\{x_{ij}, \dots, x_{nj}\} - x_{ij}}{\max\{x_{1j}, \dots, x_{nj}\} - \min\{x_{ij}, \dots, x_{nj}\}}.$$
 (14)

In the equations above, i is the assessment scheme, j is the assessment index, and x_{ij} is the corresponding magnitude of the *jth* assessment index of the *ith* scheme.

(3) The proportion of the evaluation index in the scheme is determined as follows:

$$b_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}.$$
 (15)

Here, b_{ij} is the proportion of the *jth* assessment index at the *ith* scheme.

(4) The entropy of the evaluation index is calculated as follows:

$$s_j = -k \sum_{i=1}^n b_{ij} \ln(b_{ij}),$$
 (16)

where s_j is the entropy value of the *jth* assessment index.

(5) The weight of the evaluation index is calculated as follows:

$$\omega_j = \frac{1 - s_j}{n - \sum_{j=1}^n s_j},\tag{17}$$

where ω_j is the weight coefficients of the *jth* assessment index.

2.4. The Determination of the Assessment Level. Equations (9), (10), and (16) are used in conjunction with results from reference [22] to calculate the synthetic membership degree as follows:

$$v_F(u)_j = \frac{1}{1 + \left(\sum_{i=1}^m \left[\omega_i \left(1 - \mu_F(u)_{ij}\right)\right]^p / \sum_{i=1}^m \left[\omega_i \mu_F(u)_{ij}\right]^p\right)^{f/p}}.$$
(18)

Normalizing $v_F(u)_j$ yields the magnitude of the normalized synthetic membership degree as follows:

$$V = (\nu'), \tag{19}$$

where

$$v' = \frac{v_F(u)_j}{\sum_{j=1}^m v_F(u)_j}.$$
 (20)

Finally, the assessment level can be determined based on the value of *R*:

$$R = (1, 2, \dots, c) \bullet V.$$
 (21)

2.5. The Assessment Procedure Based on the Entropy-Variable Fuzzy Set Model. The entropy-variable fuzzy sets model is applied to assess the pavement performance using the following procedures:

- (1) The eigenvalue matrix *X* and classification standard of the index are determined based on the monitoring data and correlation criteria.
- (2) The attraction range I_{ab} , the range matrix $I_{c d}$, and point value matrix F are determined according to the classification standard.
- (3) The relative difference function $D_F(\mathbf{u})$ can be calculated based on equations (8) and (9); then, the relative membership degree can be determined using equations (10) and (11).
- (4) The weights of the different indexes for the pavement performance are determined using equations (12)-(25) based on the entropy method.
- (5) The normalized synthetic membership degree matrix is determined using equations (18)–(20); finally, the magnitude of the assessment level is determined using equation (21). On the basis of *H*, if $n - 0.5 \le H \le n + 0.5$, then the result is level *n*.

3. Case Study

3.1. Engineering Background. Lanwu Highway is located in Gansu Province, China. The highway is 273 kilometers in length. The riding quality index (RQI), pavement condition index (PCI), pavement structure strength index (PSSI), skid resistance index (SRI), and antirutting index (ARI) are selected as the assessment indexes of the pavement performance of the Lanwu Highway, using five levels for the assessment classification standard: excellent (I), good (II), medium (III), inferior (IV), and bad (V); the corresponding standard value and the monitoring value of the samples are listed in Tables 1 and 2, respectively.

3.1.1. Riding Quality Index (RQI). Flatness and ruts are key factors of pavement riding quality, and the road is uneven or the depth of ruts is big; these will result in the decrease of riding safety, and the riding quality can reflect the fast, safe, comfort, and economic function of pavement, so it is selected as the quality index of pavement performance.

3.1.2. Pavement Condition Index (PCI). Pavement condition index (PCI) is defined as the index of integrity degree of pavement, and it can represent the quality of pavement performance.

3.1.3. Pavement Structure Strength Index (PSSI). According to the definition of preventive maintenance, preventive maintenance is only applied to functional disease of surface, such as cracks and slight ruts. So, the good and bad of pavement structure strength have a great influence on preventive maintenance; only if pavement structure strength index (PSSI) meets the evaluation standards, preventive maintenance can be performed; otherwise, other maintenance methods can be adopted.

TABLE 1: Classification standard of the assessment model.

Level	RQI	PCI	PSSI	SRI	ARI
Ι	100-85	100-85	100-85	100-85	100-85
II	85-70	85-70	85-70	85-70	85-70
III	70-55	70-55	70-60	70-60	70-55
IV	55-40	55-40	60-40	60-40	55-40
V	40-0	40-0	40-0	40-0	40-0

TABLE 2: The monitoring values of samples.

Sample	RQI	PCI	PSSI	SRI	ARI
1	50.3	63.6	45	90.9	70.6
2	66.5	40	66.9	70.3	79
3	86.6	82.1	86.7	44	68.3
4	62.6	70.4	67	88.6	86.3
5	88.1	77	73.6	51	50.1
6	70.7	91	86.3	96.6	95.6

3.1.4. Skid Resistance Index (SRI) and Antirutting Index (ARI). Skid resistance index (SRI) and antirutting index (ARI) have been widely applied to assess the quality level of pavement performance. They are important features of pavement performance.

3.2. The Construction of the Assessment Frame. The assessed pavement performance affects the quality of pavement construction as well as human life and property security. Consequently, the quality assessment of pavement performance is extremely important.

A novel quality assessment method of pavement performance is proposed based on the variable fuzzy sets model, as presented in Figure 2. First, a complete assessment index system is formulated to evaluate the quality level of pavement performance. Second, the weight of each assessment index is determined by using an entropy weight theory. Third, the relative membership degree is determined using the variable fuzzy sets theory. Then, magnitudes of the synthetic certainty degree are determined, and finally, the quality level of the pavement performance is obtained.

3.3. Determination of the Quality Level of Pavement Performance

3.3.1. Calculation of Three Matrix. The proposed assessment procedure is used to determine the quality level of the pavement performance of the Lanwu Highway; the results in Table 1 are used in conjunction with equation (4) to determine the attractive sphere I_{ab} as follows:

	[100	85]	[85	70]	[70	55]	[55	40]	[40	[0]	
	[100	85]	[85	70]	[70	55]	[55	40]	[40	0]	
$I_{ab} =$	[100	85]	[85	70]	[70	60]	[60	40]	[40	0].	(22)
	[100	85]	[85	70]	[70	60]	[60	40]	[40	0]	
	[100	85]	[85	70]	[70	55]	[55	40]	[40	0]]	

Equation (5) is used to determine the matrix for the range I_{de} as follows:



FIGURE 2: The assessment process for the pavement performance level.

$$I_{de} = \begin{bmatrix} \begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 55 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 55 & 0 \end{bmatrix} \\ \begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 55 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 55 & 0 \end{bmatrix} \\ \begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 60 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 60 & 0 \end{bmatrix} \\ \begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 60 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 60 & 0 \end{bmatrix} \\ \begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 55 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 55 & 0 \end{bmatrix} \end{bmatrix}.$$

$$(23)$$

Equations (6) and (7) are used to determine the point value matrix F as follows:

$$F = \begin{bmatrix} 100 & 81.25 & 62.5 & 43.75 & 0 \\ 100 & 81.25 & 62.5 & 43.75 & 0 \\ 100 & 81.25 & 65 & 45 & 0 \\ 100 & 81.25 & 65 & 45 & 0 \\ 100 & 81.25 & 62.5 & 43.75 & 0 \end{bmatrix}.$$
 (24)

3.3.2. The Determination of the Relative-Membership-Degree Matrix. In the first procedure, equations (8) and (9) are used to determine whether a monitoring datum (the assessment index) presented in Table 2 is located to the left or right of point *F*; using the data of sample 1 as an example, for i = 1, $\begin{bmatrix} a & b \end{bmatrix}_{1j} \begin{bmatrix} d & e \end{bmatrix}_{1j}$, the point value F can be expressed as follows:

$$\begin{bmatrix} a & b \end{bmatrix}_{1j} = (\begin{bmatrix} 100 & 85 \end{bmatrix} \begin{bmatrix} 85 & 70 \end{bmatrix} \begin{bmatrix} 70 & 55 \end{bmatrix} \begin{bmatrix} 55 & 40 \end{bmatrix} \begin{bmatrix} 40 & 0 \end{bmatrix}), \\ \begin{bmatrix} d & e \end{bmatrix}_{1j} = (\begin{bmatrix} 100 & 70 \end{bmatrix} \begin{bmatrix} 100 & 55 \end{bmatrix} \begin{bmatrix} 85 & 40 \end{bmatrix} \begin{bmatrix} 70 & 0 \end{bmatrix} \begin{bmatrix} 55 & 0 \end{bmatrix}),$$
(25)

$$F = \begin{bmatrix} 100 & 81.25 & 62.5 & 43.75 & 0 \end{bmatrix}.$$

For $x_1 = 50.3$, $a_{11} = 100$, $b_{11} = 85$, $d_{11} = 100$, $e_{11} = 70$, and $F_{11} = 100$, x_1 is located outside the intervals, so $\mu_F(u_{11}) = 0$; for $a_{12} = 85$, $b_{12} = 70$, $d_{12} = 100$, $e_{12} = 55$, and $F_{12} = 81.25$, x_1 is located in the outside the intervals, so $\mu_F(u_{12}) = 0$; when $a_{13} = 70$, $b_{13} = 55$, $d_{13} = 85$, $e_{13} = 40$, and $F_{13} = 62.5$, x_1 is located to the left of F_{13} and belongs to $[b_{13} \ e_{13}]$; then, based on equation (11), the relative membership degree can be obtained as $\mu_F(u_{13}) = 0.35$.

Similarly, the relative-membership-degree matrix of sample 1 can be written as follows:

$$\mu_F(u_{1j}) = \begin{bmatrix} 0 & 0 & 0.35 & 0.709 & 0.157 \\ 0 & 0.287 & 0.927 & 0.213 & 0 \\ 0 & 0 & 0.125 & 1 & 0 \\ 0.697 & 0.303 & 0 & 0 & 0 \\ 0.02 & 0.527 & 0.48 & 0 & 0 \end{bmatrix}.$$
 (26)

3.3.3. The Determination of the Weight Coefficients of Different Indexes. The results presented in Table 2 are used in conjunction with equation (15) to yield the specific gravity matrix for each index, as listed in Table 3.

TABLE 3: The synthetic parameters for pavement performance.

Sample	RQI	PCI	PSSI	SRI	ARI
1	0.1184	0.15	0.1058	0.2059	0.1569
2	0.1565	0.0943	0.1572	0.1593	0.1756
3	0.2039	0.1936	0.2038	0.0997	0.1518
4	0.1474	0.166	0.1575	0.2007	0.1918
5	0.2074	0.1816	0.173	0.1155	0.1114
6	0.1664	0.2146	0.2028	0.2188	0.2125

TABLE 4: The entropy matrix.

Index	RQI	PCI	PSSI	SRI	ARI
Index entropy	0.9901	0.9841	0.9883	0.9778	0.9893

TABLE 5: The weight coefficient matrix.

Index	RQI	PCI	PSSI	SRI	ARI
Weight coefficients	0.1406	0.2262	0.1662	0.3147	0.1523

TABLE 6: The comprehensive relative membership vector.

f & p			$v_F(u)$	1	
f = 1, p = 1	0.4762	0.2405	0.3514	0.3141	0.0221
f = 1, p = 2	0.3783	0.2828	0.3833	0.3362	0.0454
f = 2, p = 1	0.0756	0.0911	0.1213	0.1734	4.99×10^{-4}
f = 2, p = 2	0.2702	0.1346	0.2787	0.1988	0.0023

The results in Table 3 are used in conjunction with equation (16) to calculate the index entropy matrix of every index, as listed in Table 4.

Equation (17) is used to calculate the weight coefficients of the indexes, as listed in Table 5.

It can be found in Table 5 that skid resistance index (SRI) is the most important index, and pavement condition index (PCI) is the second important index; as the most important index, SRI is the comparative main criterion, which is compared with other 3 indices separately.

3.3.4. Determination of the Comprehensive Relative Membership Vector and Normalization. Equation (18) is used in combination with the matrix to calculate the comprehensive relative membership matrix, as listed in Table 6.

Equations (19) and (20) are used to determine the normalized comprehensive relative membership vector, as listed in Table 7.

3.3.5. Determination of the Quality Level of the Pavement *Performance*. Equation (21) is used in combination with the results presented in Table 7 to calculate the ranking feature values of sample 1 as follows:

The feature values presented in Table 8 have a mean of 2.5469 and range between 2.5 and 3.5. Thus, the pavement performance for sample 1 is level III according to the current model.

Table 9 lists the feature values of samples 2, 3, 4, 5, and 6 that are similarly calculated.

TABLE 7: The normalized comprehensive relative membership vector.

f & p			v		
<i>f</i> = 1, <i>p</i> = 1	0.3391	0.1713	0.2502	0.2237	0.0157
f = 1, p = 2	0.2653	0.1983	0.2687	0.2357	0.0318
f = 2, p = 1	0.1637	0.1972	0.2626	0.3754	0.0011
f = 2, p = 2	0.3054	0.1522	0.315	0.2247	0.0026

The assessment results for the pavement performance are verified against those obtained using other methods (Table 10).

Tables 9 and 10 list the results of applying the variable fuzzy set assessment model to assess the pavement performance quality. In Table 10, the quality levels of the pavement performance for samples 1 to 6 are III, III, III, III, III, and I. That is, the quality level of the pavement performance is medium for samples 1, 2, 3, and 5, excellent for sample 6, and good for sample 4. These results show that the quality of the comprehensive pavement performance meets construction requirements; as the quality score reaches up to 100% and the good and excellent scores are 13.3%, no measurement is required to validate the pavement performance quality.

The comparative assessment results represented in Table 10 show that results obtained by using the variable fuzzy sets method are basically consistent with the current specification for the different samples, except for sample 3. The accuracy rate of the proposed method reaches 84%, which is higher than those obtained using the extension evaluation [6] and the intuitionistic fuzzy sets model [23]. Therefore, it is feasible to estimate the quality level of pavement performance by using the entropy weight-variable fuzzy sets model. The proposed method both provides accurate results and additional details about the pavement performance levels. For example, the pavement condition index l (PCI) of sample 5 is 77, which corresponds to level II according to Table 1. The degree of membership of the other indexes obtained using the variable fuzzy sets model belongs to level III; thus, there is a larger probability that sample 5 has a quality level of III than I, IV, and II and V. That is, the quality level of sample 5 can only be assigned to level III and cannot be assigned to levels I, IV, and II and V. Furthermore, the quality level of sample 5 is more likely to be III than those of samples 1, 2, and 3, because the mean ranking feature value of sample 5 for level III (2.9954) is higher than those of samples 1 (2.5649), 2 (2.8428), and 3 (2.7615). In summary, the results obtained by using the entropy weight-variable fuzzy sets model both reflect the quality level accurately and can be used to rank the quality ranking of pavement performance for different samples with the same level.

4. Discussion and Comparative Analysis

- 4.1. Comparison with Existing Studies
 - The variable fuzzy sets model is suggested to assess the quality level of pavement performance, and good results are obtained. However, due to lack of information, the uncertain human mind, and time

1

2

3

4

5

6

C	Ranking feature value						
Sample number	f = 1, p = 1	f = 1, p = 2	f = 2, p = 1	f = 2, p = 2	Mean value		
1	2.4056	2.5698	2.853	2.4666	2.5649		

TABLE 9: Results obtained by applying the assessment model to 6 samples. Ranking feature value

TABLE 8: The feature values of sample 1

Sample number Mean value = 1, p = 1= 1, p = 2= 2, *p* = = 2, p = 22.4056 2.5698 2.853 2.4666 3.0234 2.8099 2.8914 2.6465 2.6898 2.9449 2.4839 2.9419 2.0047 2.1962 2.1312 2.2102 2.909 2.9988 2.9575 3.1163

1.4923

TABLE 10: Comparison of results obtained using the different models.

1.1489

Sample number	Proposed method	Current specification	Extension evaluation	Intuitionistic fuzzy sets model
1	III	III	IV	IV
2	III	III	III	III
3	III	II	II	II
4	II	II	III	III
5	III	III	II	II
6	Ι	Ι	II	Ι

complexity, the decision experts (DEs) cannot provide accurate results for the subjective methods such as best-worst method (BWM) [24], level-based weight assessment (LBWA) [25], full consistency method (FUCOM) [26], and the stepwise weight assessment ratio analysis (SWARA) [27]. The proposed model not only considers the unreliability or reliability of the problem but also solves some degrees of uncertainty and ambiguity of datum, thus conquering this concern. So, it has great advantages over these subjective ones. For this engineering example, the proposed model accurately conveys the risk degree of pavement performance by adopting the eigenvalue of level H, so it is much stricter in the superior grade, and the integrity is improved to assess the quality level of pavement performance.

1.4088

(2) In comparison with the traditional extension evaluation model, the fuzziness and randomness of evaluating index are considered, and interval-oriented evaluation criteria are adopted. So, the proposed method improves the reliability of the assessment process and effectively detects the quality status of pavement performance.

4.2. The Advantages and Limitations of the Proposed Model. By comparing the appropriate methods, the advantages of the suggested method can be summarized as follows:

(1) The proposed method can accurately convey the risk degree of pavement performance, so it has higher accuracy

(2) Compared with the traditional method, its assessment process has higher reliability and efficiency

1.1701

However, the suggested model still has some limitations. For example, the calculation is complicated, and multiple variable parameters are required to calculate the degree of difference; thus, it has limited application, and the theory has still great space for improvement in the future. But when the classification standard of the assessment index is an interval and not a point, the proposed model can be applied to assess the quality level of other real-life problems.

5. Conclusions and Future Scope

The riding quality index (RQI), pavement condition index (PCI), pavement structure strength index (PSSI), skid resistance index (SRI), and the antirutting index (ARI) are used in conjunction with the entropy weight-variable fuzzy sets model to develop a novel assessment method for the quality level of pavement performance. First, the relative membership matrix of the assessment sample is determined. Then, the weighting coefficients of the different indexes are obtained by using the entropy weighting method. Finally, the quality level of the pavement performance is determined from the mean ranking feature value.

The proposed method is applied to assess the quality level of pavement performance. Compared with the results obtained using the current specifications, extension method, and the intuitionistic fuzzy sets model, the assessment results obtained using the variable fuzzy sets method are basically consistent with the current specification with an accuracy of up to 84%. The quality levels of pavement performance for

2.5649

2.8428

2.7615

2.1356

2.9954

1.305

samples 1 to 6 are III, III, III, III, III, and I. That is, the quality of the comprehensive pavement performance meets the requirements, and no measurement is required to validate the pavement performance quality.

Overall, the results assessed by using the variable fuzzy sets method are basically consistent with the current specification for the different investigated samples, except for sample 3. The results obtained by using the entropy weightvariable fuzzy sets model both accurately reflect the quality level and can be used to rank the quality ranking of pavement performance for different samples with the same level. The proposed method can accurately convey the risk degree of surrounding rocks; in comparison with the traditional method, its assessment process has higher reliability and efficiency. But its calculation is complicated, and multiple variable parameters are required to calculate the degree of difference, so the proposed method can still be improved in the future.

In future work, the concept of spherical fuzzy sets can be applied. Its range varies from standard fuzzy sets to spherical fuzzy sets, and this will be my future direction to assess the quality level of pavement performance.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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