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Research on the assessment method of road and bridge health monitoring data based on fuzzy mathematical algorithm and multi-factor analysis

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Abstract Highway and bridge pavement engineering materials are facing great aging, depletion and disease pressure under the cross-impact of traffic load, climate and geological environment, etc. Therefore, real-time monitoring of pavement health is particularly important. In this paper, based on the fuzzy mathematical algorithm and multi-factor analysis, the road and bridge health monitoring data assessment method is explored. First, the hierarchical structure of road and bridge health comprehensive monitoring indexes was constructed by combing the literature and utilizing the hierarchical analysis method. Then, the indicators were weighted by combining the G1 method and DEMATEL method. Finally, the cloud model was used to conduct a fuzzy comprehensive evaluation of road and bridge health. The results of the example application show that the method of combining the G1 method and DEMATEL method for indicator assignment in this paper takes into account the causal relationship between each indicator, and the results of the comprehensive weighting are more scientific and effective, which is of practical significance for assessing the health status of road and bridge. In addition, the fuzzy comprehensive evaluation model based on the cloud model in this paper can make up for the shortcomings of the traditional evaluation of the road and bridge health status reflecting insufficiently, and the mean value of the fuzzy evaluation agreement ratio of each data set is greater than 0.87, and the fuzzy evaluation agreement ratio increases year by year with the passage of time. In addition, this paper explores the shortcomings of the methods used and provides directions for further improvement of the model.

Index Terms G1 method, dematel method, cloud modeling, road and bridge health assessment

I. Introduction

Road and bridge is a large civil infrastructure with huge investment and long service life, so the safety of road and bridge use has a significant impact on the national economy. Due to the role of climate, disaster, environment and other natural factors and increasing traffic flow, and heavy vehicles, overweight vehicles across the bridge number of increasing, while with the bridge age continues to grow, road and bridge structure will inevitably produce natural aging, damage accumulation, its safety and use of performance is bound to deteriorate, and even lead to sudden accidents [1]-[4]. Therefore, it is very necessary to carry out safety monitoring and assessment of the operation condition of road and bridge and other large civil infrastructures. Due to the large size of road bridges, more constraint points, and complex structural deformation, a comprehensive assessment of their health status requires understanding the state of road bridges from different aspects (e.g., vibration, disturbance, strain, etc.) [5], [6]. By monitoring and evaluating the structural condition of road bridges, it can trigger early warning signals for road bridges under special climate and traffic conditions or when the operating condition of road bridges is seriously abnormal, and provide the basis and guidance for road bridge maintenance, repair and management decisions [7], [8]. Road and bridge health monitoring according to the road and bridge structural safety, applicability and durability assessment needs and road and bridge management, decision-making departments of the information needs, and combined with the current actual economic conditions and road and bridge on-site monitoring conditions, based on the practicality and reliability, to a certain extent, taking into account its advanced, and taking into account the relationship between the cost - benefit, to determine the various monitoring programs extremely assessment methods [9]-[12].

There are three broad categories of existing methods for assessing the state of health of road bridges, one is visual-based assessment. Bertola and Brühwiler [13] synthesized the degradation and failure of bridge elements to visually assess the condition of bridges, which improves the accuracy of the assessment of the overall structure of the bridge, and can also be used as a basis for making decisions on the management of bridge assets. However, visual assessment is susceptible to the subjective influence of engineers and may be over-assessed and incomplete. The second is the assessment based on single-factor thresholds or totality. Nasim et al [14] used vibration data from non-contact interferometric radar as input for health assessment of bridge bearings under a simplified analytical model. With the help of condition inspection reports of bridges in the region, Xia et al [15] analyzed and integrated the data in the reports to establish a network-level methodology for the overall condition assessment of bridges, which not only performs a health assessment, but also provides guidance for bridge maintenance management. Zegeye-Teshale et al [16] introduced assessment methods for suspected cracking of pavements, mainly using a combination of multisensor and nondestructive testing techniques with subsurface penetrating radar, to assess the health of the roadway by capturing data on cracking characteristics of the pavement and analyzing the data. These methods only consider the assessment results in the single-factor state, ignoring the chain reaction of road and bridge damage and the damage or aging behavior of multi-factor fusion, which is prone to misjudgment. Third, model-based assessment. Yang et al [17] constructed a hybrid classification model to categorize a large amount of fuzzy labeled data in bridge health assessment, thus forming a multi-layer hybrid approach for automated bridge health assessment.Rogulj et al [18] combined expert evaluation, fuzzy weighted geometric mean, and hierarchical analysis to assess the health of historical bridges in a fully structured way, and for this purpose, they constructed an expert knowledge-paved of fuzzy assessment system. Mușat and Bitir [19] assessed the state of forest roads under three loading scenarios with a finite element modeling approach, which indicated that the layer thickness of the road is an effective way to mitigate the road deformation.Cui et al [20] calculated the weights of road tunnel health assessment metrics through an improved hierarchical analysis method and introduced an improved cloud model to jointly assess the tunnel health condition, in which the assessment indexes contain both static and dynamic parameters. The above model-based assessment methods are difficult to cope with the assessment of road and bridge health status under the conditions of material nature, environmental randomness, and multifactors.

Fuzzy mathematical algorithm is a mathematical tool for dealing with fuzzy problems. It quantifies uncertainty and ambiguity into numerical values by introducing the concept of fuzzy sets, which can be used for analysis and decision making [21]. Since fuzzy mathematical algorithms are expanding the traditional binary logic into multivariate logic, which enables problems to be better described and solved, they have advantages in fuzzy and uncertain problem solving, and they can be used in road and bridge for safety risk assessment of road construction, road performance evaluation, and life cycle evaluation of bridges [22]-[24]. Therefore, it is an effective solution to face the fuzzy, dynamic and stochastic problems in road and bridge health assessment.

This paper successfully constructs a road bridge health condition assessment model based on hierarchical analysis, G1 method, DEMATEL method and cloud model. The model uses the hierarchical analysis method to build the hierarchical structure of assessment indicators, utilizes the G1 method and the DEMATEL method to realize the combination of indicator assignment and causality analysis, and realizes the fuzzy evaluation of road and bridge health status based on the cloud model. In addition, this paper also compares and analyzes the evaluation results of the model by analyzing two defined evaluation indexes, namely, fuzzy evaluation consistency ratio and fuzzy evaluation credibility, and carries out error analysis and simulation analysis, so as to summarize the deficiencies of the model and the space for improvement.

II. Hierarchy of indicators for integrated road and bridge health monitoring

This chapter combines the literature to analyze the influence of four types of infrastructure and traffic environment, namely road facilities, bridge facilities, tunnel facilities, and traffic safety facilities, on the health status of road and bridge, summarizes 21 influencing factors, and combines with the hierarchical analysis method [25], to establish a comprehensive monitoring index system for road and bridge health as shown in Table 1. The target layer is the comprehensive monitoring of road and bridge health (A), and the guideline layer includes five dimensions of road facilities (B1), bridge facilities (B2), tunnel facilities (B3), traffic safety facilities (B4), and traffic environment (B5). The index layer is further subdivided into 21 indicators, which are subgrade condition (C1), pavement damage (C2), rutting (C3), risk road section (C4), bridge superstructure (C5), bridge substructure (C6), bridge deck system (C7), civil facilities (C8), power supply and distribution facilities (C9), monitoring and communication facilities (C10), fire protection facilities (C11), ventilation facilities (C12), lighting facilities (C13), protection facilities along the line (C14), Traffic Signs and Markings (C15), Sight Guidance Facilities (C16), Isolation and Closure Facilities (C17), Street Lights (C18), Weather Conditions (C19), Traffic Flow (C20), Vehicle Distribution (C21).

Table 1: Comprehensive monitoring index system of road and bridge health

Target layer	Criterion layer	Index layer
Comprehensive monitoring of road and bridge health (A)	Road facilities (B1)	C1
		C2
		C3
		C4
	Bridge facility (B2)	C5
		C6
		C7
	Tunnel facility (B3)	C8
		C9
		C10
		C11
		C12
		C13
	Traffic safety facilities (B4)	C14
		C15
		C16
		C17
		C18
	Traffic environment (B5)	C19
		C20
		C21

III. Road and bridge health assessment based on G1-DEMATEL-cloud modeling

In order to utilize the monitoring data to effectively assess the health condition of road bridges, this paper combines the G1 method and DEMATEL method to calculate the weights of indicators, and adopts a cloud model for comprehensive assessment.

III. A. G1 method for determining weights

The G1 method [26] avoids the problems of cumbersome calculations and the need for consistency tests in the hierarchical analysis method, and compared with the DEMATEL method [27], it also reduces the problem of experts' errors of judgment due to too many indicators. Its specific steps are as follows:

(1) Determine the order relationship. If there are n evaluation indicators for the evaluation object, for the set of evaluation indicators $C=\{C_1,C_2,\cdots,C_n\}$, the expert first selects 1 indicator from it that is considered to be the most important as C_1^*, and then continues to select the 1 most important indicator from the remaining indicators. After $n-1$ selections, 1 corresponding ordinal relation is derived as:

$$C_1^*>C_2^*>\cdots>C_n^* \tag{1}$$

(2) Determine the relative importance S_k of evaluation indicator C_{k-1} and C_k. The values of S_k are 1.0, 1.2, 1.4, 1.6 and 1.8, which indicate that the indicator C_{k-1} is equally important, slightly important, obviously important, strongly important and extremely important with the indicator C_k, respectively. The calculation formula is as follows:

$$S_k=\frac{W_{k-1}}{W_k},\left(k=n,n-1,n-2,\cdots,3,2\right) \tag{2}$$

Where: W_k is the weight of the kth evaluation index.

(3) Determine the weight coefficient. The weight of evaluation indicator C_n is W_n:

$$W_n=\left(1+\sum_{k=2}^{n}\prod_{i=k}^{n}S_i\right)^{-1} \tag{3}$$

where: S_i is the relative importance of the $k-1$th indicator to the kth indicator.

The other indicators are weighted:

$$W_{k-1}^*=S_k\times W_k^*\left(k=2,3,4,\cdots,n-1,n\right) \tag{4}$$

where W_k^* is the weight of the k th indicator.

III. B. DEMATEL method for determining composite weights

The steps for determining the combined weights using the DEMATEL method are as follows:

(1) Determine the degree of direct influence between the elements. Experts use a score of 0 to 5 to indicate that 2 indicators have no influence on each other, weak influence, relatively weak influence, average influence, strong influence and very strong influence, respectively.

(2) Get the normalized direct influence matrix B according to equation (5):

$$B=\left(b_{ij}\right)_{n\times n} \tag{5}$$

where: b_{ij} is each factor value of the normalization matrix, $b_{ij}=\dfrac{c_{ij}}{c_i'}$. c_i' is the maximum row sum of the direct influence matrix, $c_i'=\max\left\{\sum_{j=1}^{n}c_{ij}\right\}\left(i=1,2,\cdots,n\right)$. c_{ij} is the value of each factor of the direct influence matrix.

(3) Construct the composite influence matrix T:

$$T=B\left(I-B\right)^{-1} \tag{6}$$

where: I is the unit matrix.

The centrality h_i is found using the combined influence matrix T, the larger the centrality, the more important the factor is:

$$h_i=f_i+g_i\left(i=1,2,\cdots,n\right) \tag{7}$$

where: $f_i=\sum_{j=1}^{n}f_{ij}(i=1,2,\cdots,n)$, f_{ij} is the synthesized impact matrix row sum, $g_i=\sum_{j=1}^{n}g_{ij}(i=1,2,\cdots,n)$, and g_{ij} is the synthesized impact matrix column sum.

(4) Comprehensive impact calculation:

$$X_i=h_iw_i\Big/\sum_{j=1}^{n}h_jw_j\quad\left(i=1,2,\cdots,n\right) \tag{8}$$

where: w_i is the weight calculated by the G1 method, and h_jw_j is the product of the centrality of each indicator and the corresponding G1 method weight.

III. C. Cloud modeling based road and bridge health assessment

The health condition of road and bridge is dynamic, and the judgment of the degree of influence of each evaluation index on the health of road and bridge is subjective, and the evaluation process is random and fuzzy. As a new evaluation method, cloud model can combine the fuzzy and randomness, complete the conversion of uncertainty between qualitative and quantitative, and reflect the evaluation results more objectively and scientifically [28]. Therefore, this paper adopts the cloud model to carry out a comprehensive assessment of the health condition of road and bridge.

Let U be an argument domain with quantitative data representation and C be a qualitative concept associated with U, if the quantitative value $x\in U$, x is a one-shot random realization of the qualitative concept C, and the degree of affiliation $\mu\in[0,1]$ of x to C is a fuzzy or random number with a certain regularity. The cloud drops the combination of a specified quantity value x and the degree of affiliation μ, denoted as $(x,\mu(x))$.

Clouds transform qualitative concepts into quantitative values, i.e., into points in the argument space, which is a discrete transformation process with randomness that can be represented by a probability distribution function. In the argument space, a large number of cloud droplets constitute a cloud, which has shape and no boundary, similar to clouds in nature. Normal distribution phenomenon exists widely in nature, and normal cloud model is widely used because it can reflect the ambiguity and uncertainty in it. The normal cloud model completely expresses the ambiguity of the concept and the randomness of the affiliation degree through three numerical characteristic parameters, namely, expectation Ex, entropy En, and hyperentropy He, so as to realize the conversion between qualitative concepts and quantitative data. Among them, Ex reflects the center of gravity of cloud droplets. En is jointly determined by the randomness and fuzziness of qualitative concepts, which is a measure of the randomness of concepts on the one hand, reflecting the discrete degree of cloud droplets, and on the other hand, it is a measure of the fuzziness of qualitative concepts, reflecting the range of values of cloud droplets in the space of the thesis domain which can be accepted by the concepts. He, i.e., the entropy of entropy, depends on the vagueness and randomness of entropy, which indirectly reflects the thickness of cloud droplets; the thicker the cloud droplets are, the greater the superentropy is, and the greater the randomness and vagueness are.

The specific steps for road and bridge health assessment using the cloud model are as follows:

Step1: Calculate the evaluation index system index weights. Combine the G1 method and DEMATEL method to assign weights to the road bridge health monitoring indicators.

Step2: Calculate the cloud model indicator affiliation degree. Conditional cloud generator is used to calculate the affiliation degree of each quantitative evaluation index data value in each evaluation level. Firstly, the 3 characteristic parameters of quantitative indicators are calculated. Let there are a total of m indicators and q grades, the expectation, entropy and hyperentropy are calculated as:

$$\begin{cases} Ex_{ij} = \dfrac{S_{ij,\max} + S_{ij,\min}}{2} \\ En_{ij} = \dfrac{S_{ij,\max} - S_{ij,\min}}{6} \\ He = C \end{cases} \tag{9}$$

where: Ex_{ij} , En_{ij} are the expectation and entropy of the i th metric in the j th rank, $i = 1,2,\cdots,m$, $j = 1,2,\cdots,q$, respectively. $S_{ij,\max}$, $S_{ij,\min}$ are the maximum and minimum bounds of the i th indicator in the j th rank, respectively. He is the hyperentropy, determined experimentally or empirically, and is a constant value. q is the number of indicator level classifications.

For $(-\infty, S_{ij,\min})$ or $\left(S_{ij,\max}, +\infty\right)$, i.e., grades without lower or upper bounds, the value of the default side parameter of the indicator should be determined according to the bounds of the indicator's data values before calculating the characteristic parameters.

Then calculate the affiliation of the indicator in each rank, input the indicator value, generate p normal random numbers, and calculate the average of the affiliation of p cloud droplets as the affiliation of each rank, the calculation formula is:

$$\mu_{ij}(x) = \frac{\sum_{k=1}^{p} \mu_{ijk}(x)}{p} \tag{10}$$

$$\mu_{ijk}(x) = \exp\left(\frac{-(x_i - Ex_{ij})^2}{2En_{ijk}'^2}\right), j = 1,2,\cdots,n \tag{11}$$

$$En_{ijk}' = randn(1) \cdot He + En_{ij} \tag{12}$$

where: $\mu_{ijk}(x)$ is the affiliation of element x to the k cloud droplet in the j th rank of the i th metric, $\mu_{ij}(x)$ is the affiliation of element x to the j th rank of the i th metric, and En_{ijk}' is the generating k th i th metric of the j th rank normal random number.

The affiliation of each indicator at each level was normalized using Eq. (13) to generate the indicator level affiliation matrix $D = \left(\mu_{ij}^{*}\right)_{m\times q}$:

$$\mu_{ij}^{*}(x) = \frac{\mu_{ij}(x)}{\sum_{j=1}^{q} \mu_{ij}(x)} \tag{13}$$

For qualitative evaluation indicators, the health level to which they belong is determined through on-site research, and the degree of affiliation is set at 1.

Step3: Determine the evaluation level. Multiply the evaluation indicator weight vector by the indicator level affiliation matrix to get the affiliation of road and bridge health in each evaluation level:

$$D_{total} = w_i \left(\mu_{ij}^{*}\right)_{m\times q} \tag{14}$$

where: D_{total} is the affiliation vector of road and bridge health in each assessment level, and w_i is the weight of the i th indicator for the target level. The grade corresponding to the maximum affiliation is the final road and bridge health assessment grade.

IV. Application and analysis of examples

In this paper, the road and bridge system in X city of L province is selected as the research object, and the weights of road and bridge health monitoring indexes are determined by combining the G1 method and the DEMATEL method, and the monitoring data of lane 1 and lane 2 of a certain road section are selected to evaluate the road and bridge health status based on the cloud model.

IV. A. Determination of Indicator Weights for Comprehensive Road and Bridge Health Monitoring

IV. A. 1) G1 weighting results

By relevant experts and on-site technicians, the importance of each indicator is evaluated according to the actual situation of road and bridge health monitoring and management, and calculated according to the steps to get the results of the indicator weights of G1 method as shown in Table 2.

Table 2: Index weights calculated by G1 method

Criterion layer	Weight	Index layer	Weight
B1	0.3249	C1	0.2983
		C2	0.2311
		C3	0.2502
		C4	0.2204
B2	0.2262	C5	0.4779
		C6	0.2816
		C7	0.2405
B3	0.2481	C8	0.2330
		C9	0.1794
		C10	0.1576
		C11	0.1511
		C12	0.1314
		C13	0.1475
B4	0.1315	C14	0.1909
		C15	0.3080
		C16	0.1605
		C17	0.1452
		C18	0.1954
B5	0.0693	C19	0.3810
		C20	0.4141
		C21	0.2049

IV. A. 2) DEMATEL weighting results

In consultation with relevant experts and city emergency managers, the direct impact matrix was determined using a three-point Likert scale. The correlations of B1~B5, Cl~C4, C5~C7, C8~C13, C14~C18, and C19~C21 indicator pieces were scored. The comprehensive influence matrix is obtained by using equation (5) and equation (6), and then the influence degree, influenced degree, center degree, and cause degree of the road and bridge health assessment indicators are calculated respectively, and then the comprehensive weights of the indicators are obtained according to equation (8), and the results of the comprehensive weights of the first-level and second-level indicators are summarized as shown in Tables 3 and 4, respectively. The largest integrated weight of the primary indicators is road facilities (B1), followed by tunnel facilities (B3), bridge facilities (B2), traffic safety facilities (B4), and traffic environment (B5).

Table 3: Results of comprehensive weights of first-level indicators

Criterion layer	Centrality Hi	G1 weight Wi	G1 weight sort	Hi×Wi	Comprehensive weight Zj	Comprehensive weight ranking
B1	5.316	0.3249	1	1.7272	0.3114	1
B2	5.235	0.2262	3	1.1842	0.2135	3
B3	6.528	0.2481	2	1.6196	0.2920	2
B4	4.637	0.1315	4	0.6098	0.1099	4
B5	5.862	0.0693	5	0.4062	0.0732	5

Table 4: Results of comprehensive weights of secondary indexes

Index layer	Influence degree	Affected degree	Centrality degree	Causation degree	Comprehensive weight
C1	2.152	1.184	3.336	0.968	0.4211
C2	1.306	0.815	2.121	0.491	0.2074
C3	1.513	0.646	2.159	0.867	0.2286
C4	0.884	0.648	1.532	0.236	0.1429
C5	1.647	1.156	2.803	0.491	0.4858
C6	1.346	1.335	2.681	0.011	0.2738
C7	1.527	1.229	2.756	0.298	0.2404
C8	0.645	1.417	2.062	-0.772	0.2240
C9	0.753	0.748	1.501	0.005	0.1256
C10	0.992	1.364	2.356	-0.372	0.1731
C11	1.256	1.805	3.061	-0.549	0.2157
C12	0.198	1.164	1.362	-0.966	0.0835
C13	0.884	1.706	2.590	-0.822	0.1781
C14	1.475	0.693	2.168	0.782	0.1731
C15	1.577	1.159	2.736	0.418	0.3526
C16	0.886	1.704	2.590	-0.818	0.1739
C17	0.205	1.169	1.374	-0.964	0.0835
C18	1.548	1.105	2.653	0.443	0.2169
C19	1.415	1.217	2.632	0.198	0.3863
C20	1.048	1.716	2.764	-0.668	0.4409
C21	1.135	1.054	2.189	0.081	0.1728

IV. A. 3) Combined weighting analysis of indicators

Comparison of the changes in the weights in Tables 2 and 4, i.e., the results of the comparison between the G1 weights and the combined weights are obtained as shown in Figure 1. According to Figure 1 and Table 4, the results of the combined weights from the combined model show a significant change in the weights of some indicators compared to the single weights obtained through the G1 method of calculation. The weights were significantly increased for roadbed condition (C1), fire protection facilities (C11), lighting facilities (C13), traffic signs and markings (C15), and traffic flow (C20), which are five indicators with relatively high influence and will have an impact on other indicators. Therefore, in the actual road and bridge health monitoring management, the combined weight of these indicators has been increased. Those with significantly lower weights are pavement damage (C2), rutting (C3), risky road sections (C4), power supply and distribution facilities (C9), ventilation facilities (C12), isolation and closure facilities (C17), and vehicle type distribution (C21), which have a relatively low degree of influence and being influenced, meaning that they are seldom affected by the other indicators or it is difficult for them to have an impact on the other indicators but they should be given focused attention. It can be seen that by combining the weights calculated by the G1 method and the DEMATEL method, and considering the causal relationship between the indicators, the results of the comprehensive weights are more scientifically valid and of practical significance for assessing the health of road bridges.

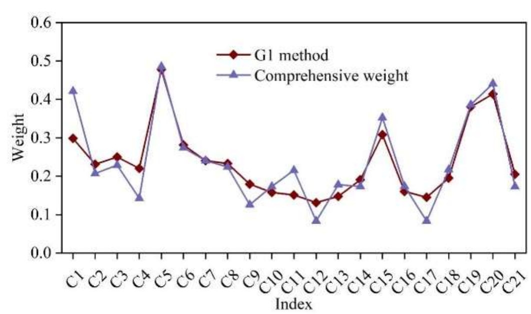


Figure 1: Comparison of G1 weight and comprehensive weight

IV. B. Analysis of causal relationships among indicators

Based on the results of the comprehensive weights of the secondary indicators in Table 4, the causal relationship between the road and bridge health assessment indicators is drawn as shown in Figure 2. The area of the circle in Figure 2 represents the comprehensive weight value of the indicators obtained from the combination model, and the larger the area of the circle represents the larger the comprehensive weight of the indicator. The horizontal coordinate of Figure 2 is the center degree, the vertical dotted line is the average value of the center degree, the larger the center degree is, the more important the indicator is in this system, the vertical coordinate is the cause degree, the horizontal dotted line is the zero scale of the cause degree, the horizontal dotted line is above the cause indicator, which affects the other indicators, and the higher up the scale, the greater the influence on the other indicators. The seven indicators located in the first quadrant, namely, roadbed condition C1, bridge superstructure C5, bridge deck system C7, traffic signs and markings C15, street lights C18, weather conditions C19, and bridge substructure C6, which are the cause indicators with high centrality and high cause degree obtained from the DEMATEL analysis, will have an impact on other indicators and should be focused on in the process of health monitoring and management of road and bridge. In the fourth quadrant, the five indicators of monitoring and communication facilities C10, fire fighting facilities C11, lighting facilities C13, sight-guiding facilities C16, and traffic flow C20 are shown in the DEMATEL results as the result indicators with high centrality and low causality, which are easy to be affected by fluctuations and can be used as the important attention indicators of the health status of the road bridge to judge whether the road bridge status is healthy or not. Healthy.

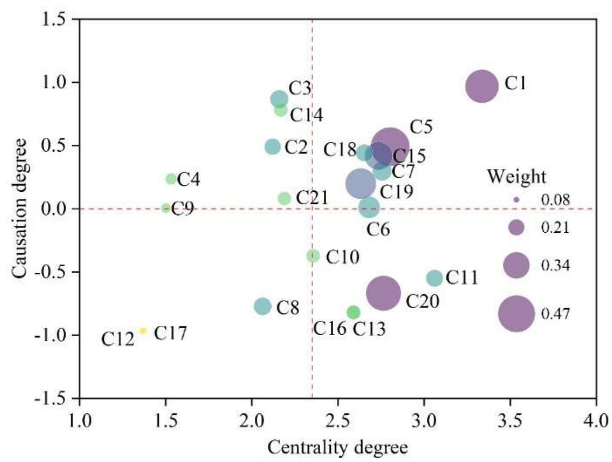


Figure 2: Causality of indicators

IV. C. Empirical evidence of fuzzy integrated evaluation

In this section, the dataset IMP11 after lane 1 interpolation in year 1 of city X is analyzed as an example. The cloud model is applied for fuzzy comprehensive evaluation and the evaluation results are obtained. The comparison between the fuzzy comprehensive evaluation results and the traditional evaluation results is shown in Table 5. Among them, 1 and 2 in the traditional evaluation grade indicate excellent and good respectively, while 1~3 in the fuzzy comprehensive evaluation grade correspond to excellent, good and medium respectively.

It can be seen that the four data that are traditionally evaluated as excellent are downgraded from excellent to good on the fuzzy evaluation results, and the four data that are traditionally evaluated as good are downgraded from good to medium on the fuzzy evaluation results. This reflects that the fuzzy comprehensive evaluation can make up for the shortcomings of the traditional evaluation in reflecting the health condition of road and bridge.

Table 5: IMP_{11} fuzzy comprehensive evaluation results

		Fuzzy evaluation level		
		1	2	3
Traditional rating level	1	294	4	0
	2	45	37	4

Calculate the proportion of agreement of fuzzy evaluation for each indicator R_{AF} by Eqs. (15)~(16):

$$I_{AF}^{(i)} = \begin{cases} 0, A_i \neq F_i \\ 1, A_i = F_i \end{cases} \tag{15}$$

$$R_{AF} = \frac{1}{n}\sum_{i=1}^{n} I_{AF}^{(i)} \tag{16}$$

Among them, F_i and A_i are the fuzzy comprehensive evaluation rubrics and traditional evaluation rubrics of the first i sample data X_i, respectively, $i = 1,2,\dots n$.

The statistical results of the fuzzy evaluation agreement ratio of the five indicators from B1 to B5 are shown in Table 6. The fuzzy evaluation agreement ratio R_{AF} of road facility B1 is 0.8665, while the R_{AF} of the four indicators of B2~B5 are 0.8759, 0.9213, 0.9958 and 0.9904, respectively, which is the lowest in comparison to the fuzzy evaluation agreement ratio of B1.

Table 6: Fuzzy evaluation consistent proportion statistics

Evaluation index	B1	B2	B3	B4	B5
RAF	0.8665	0.8759	0.9513	0.9958	0.9904

The fuzzy evaluation credibility of its comprehensive evaluation results was calculated through equations (17) to (19):

$$I_{A_k}^{(i)} = \begin{cases} 0, A_i \neq k \\ 1, A_i = k \end{cases} \tag{17}$$

$$I_{F_k}^{(i)} = \begin{cases} 0, F_i \neq k \\ 1, F_i = k \end{cases} \tag{18}$$

$$C_{F_k} = \sum_{i=1}^{n} I_{A_k}^{(i)} \Big/ \sum_{i=1}^{n} I_{F_k}^{(i)} \tag{19}$$

The results obtained are $C_{F_1} = 0.8812$, $C_{F_2} = 0.9304$, which can be seen that the fuzzy evaluation at this point in time has a higher credibility for the evaluation of rank 2 compared to rank 1.

As the cloud model has randomness in single fuzzy evaluation, the result of each evaluation is not completely consistent, for the data located in the cross position of the cloud cluster its evaluation results are affected by random factors, so this paper by repeating 600 calculations, the fuzzy evaluation of the fuzzy comprehensive evaluation results of the six data sets of fuzzy evaluation of the consistent proportion of the average as shown in Table 7. It can be seen that the fuzzy evaluation of IMP11 dataset has a lower percentage of consistency, and through 600 times of fuzzy comprehensive evaluation using the model, the average value of the fuzzy evaluation of each dataset's percentage of consistency is greater than 0.87, which indicates that the fuzzy evaluation of consistency of the same lane is roughly becoming an increasing trend over time.

Table 7: Consistent proportion of fuzzy evaluation across data sets

R_{AF}	IMP_{11}	IMP_{12}	IMP_{13}	IMP_{21}	IMP_{22}	IMP_{23}
Mean value	0.8773	0.8815	0.9314	0.9025	0.9341	0.9368

IV. C. 1) Error analysis

The results of the fuzzy evaluation of indicator B1 and the traditional evaluation are shown in Figure 3, with the horizontal axis being the traditional evaluation rubric, and the comparison shows that 42 of the data evaluated as rank 2 in the traditional evaluation were rated as rank 1 in the fuzzy evaluation, compared with only 7 data evaluated as rank 1 in the traditional evaluation and rank 2 in the fuzzy evaluation. Comparing the data in the first column of Table 5, it can be seen that because the weight of the fuzzy comprehensive evaluation of B1 is 0.3249, which is the first major weight, it makes the data traditionally evaluated as rank 2 in Table 5 have more data evaluated as rank 1 by the fuzzy comprehensive evaluation, and thus results in the fuzzy evaluation credibility of rank 1 C_{F_1} being lower than that of rank 2 fuzzy evaluation credibility C_{F_2}.

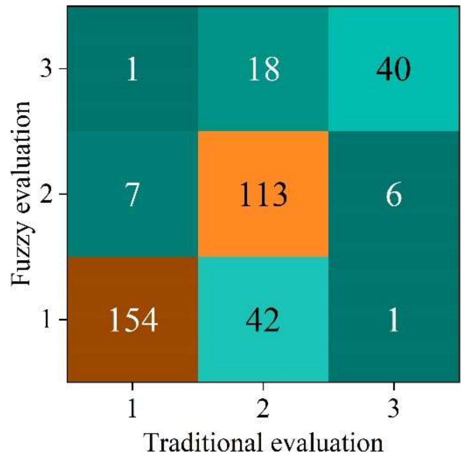


Figure 3: Comparison between traditional evaluation and fuzzy evaluation of indicator B1

The normal cloud model of IMP11 dataset B1 indicators is shown in Fig. 4, which shows that there is a large cross overlap part between its rank 1 affiliation cloud cluster and rank 2, which is a part of the point on the fuzzy evaluation is easy to cause the inconsistency with the traditional evaluation results, which in turn affects the fuzzy comprehensive evaluation results.

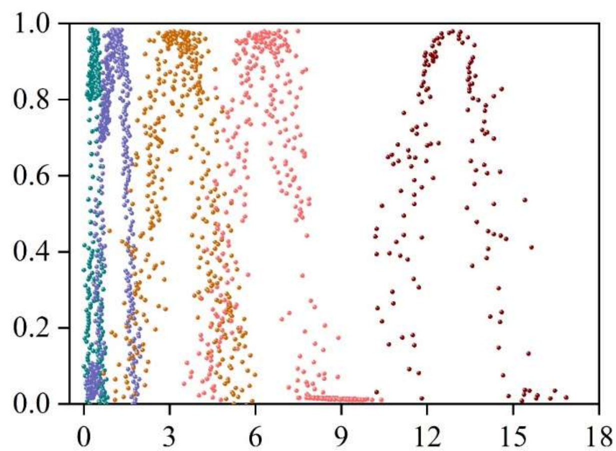


Figure 4: Index B1 Fuzzy evaluation normal cloud model

IV. C. 2) Simulation analysis

Aiming at the errors in the fuzzy comprehensive evaluation in this paper, this paper analyzes through a large number of simulation experiments, and sets the condition that two normal clouds are fused for inverse cloud computation under the condition that the parameters E_x and E_n are different, while the H_e is zero. According to the actual situation of mixing data from different overall, set the number of cloud droplets of one cloud as 12000 and the number of cloud droplets of the other cloud grows linearly with a step size of 50, and carry out the inverse cloud operation by fusing the data of the two clouds to explore the law in the estimation of the inverse cloud parameters, so as to simulate the situation of calculating the parameters through the inverse cloud algorithm after mixing the data of one cloud into the data of another cloud with a small proportion of the data of the other cloud, and calculate the parameters by means of the inverse cloud algorithm according to common The simulated data experiments are done in three cases respectively, and the three cases are briefly summarized and analyzed:

(1) Both E_x and E_n are the same

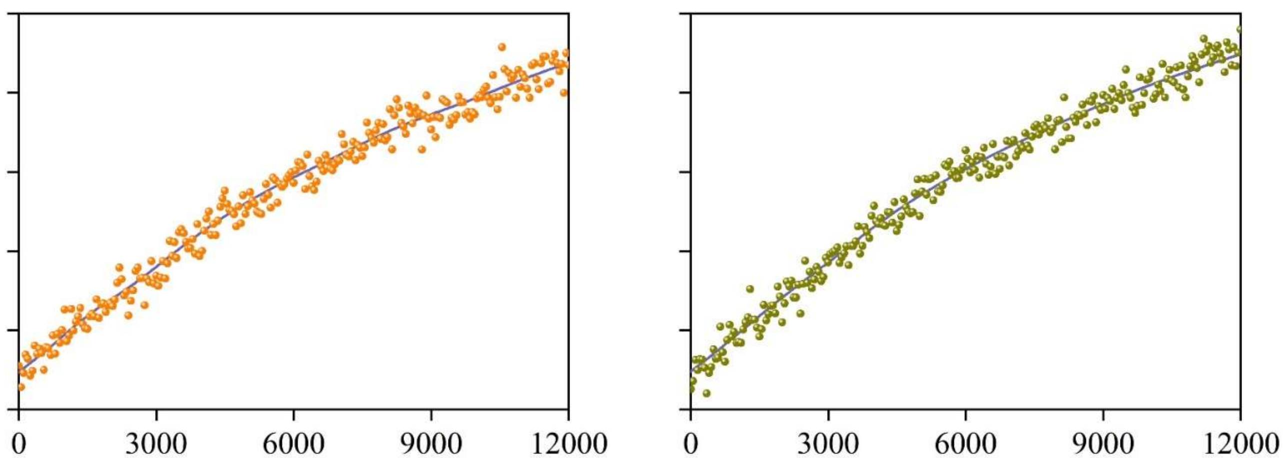
Their inverse cloud parameters E_x and E_n show a steady tendency to converge to the true values of both with the increase of the number of cloud droplets in one of the clouds, and their superentropy H_e shows a steady tendency to decrease. It is noteworthy that the trend of the three parameters tends to slow down when the cloud droplet number of one of the clouds lies in the interval [5000,7000].

(2) E_x different but E_n same

Its inverse cloud parameter E_x steadily converges to the average of the two cloud expectations as the number of cloud droplets in one of the clouds increases. E_n shows a general tendency to converge more steadily to the true value, but it is noteworthy that there is a transition from a slow increase to a subsequent sustained decrease around 5000, and H_e decreases consistently with the increase in the number of cloud drops.

(3) Both E_x and E_n are different

E_x are different and E_n are different, the two clouds perform the inverse cloud computation with the parameters $\left(E_x^1, E_n^1, 0\right)$ and $\left(E_x^2, E_n^2, 0\right)$, where $E_x^1 < E_x^2$, $E_n^1 < E_n^2$, the number of cloud droplets of the first cloud is 12,000, and the number of cloud droplets of the second cloud is gradually increasing in steps of 50, and the parameter estimates generated by the inverse cloud algorithm, $\hat{E}_x$ and $\hat{E}_n$ changes are shown in Fig. 5, where (a) and (b) represent the changes of $\hat{E}_x$ and $\hat{E}_n$, respectively. From the figure, it can be seen that as the number of cloud drops of cloud (E, E, 0) increases, $\hat{E}_x$ gradually increases and steadily converges to the mean value of E_x^1 and E_x^2, and compared with the number of cloud drops above 5,000 drops, below 5,000 drops the $\hat{E}_x$ grows faster. And $\hat{E}_n$ has the same trend and growth characteristics.



(a) The change of $\hat{E}_x$ (b) The change of $\hat{E}_n$

Figure 5: Inverse cloud parameters $\hat{E}_x$ and $\hat{E}_n$ in simulation operation

The variation of the inverse cloud parameter $\hat{H}_e$ in the simulation operation is shown in Fig. 6. The estimated value of the parameter $\hat{H}_e$ shows an upward trend, and the number of cloud droplets shows a continuous upward trend below 5000, and its value stabilizes in the interval of [5000,12000].

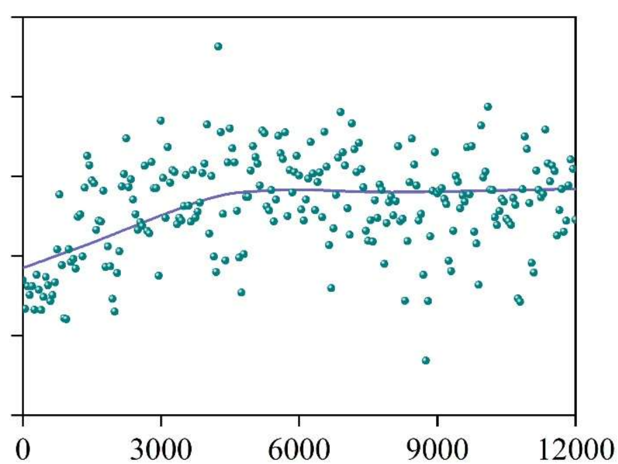


Figure 6: Inverse cloud parameter $\hat{H}_e$ in simulation operation

By continuously changing the cloud parameters for a large number of simulations, when the two normal population data are mixed, when the parameters E_x and E_n are estimated by the inverse cloud algorithm, when the proportion of the second population data in the first population data is less than a certain value, the estimated values of the parameters E_x and E_n will be too large, and the parameter H_e will also rise too quickly , the distortion in the estimation of the parameter E_x will lead to a position shift, while the large estimation of E_n will lead to an increase in the span of the cloud cluster, and the large estimation of H_e will make the cloud mass thicker, so the possibility of applying the cloud model to calculate the membership degree of the data near the critical boundary of the index interval will be greatly increased, which will affect the results of fuzzy evaluation, and the error of the evaluation results of index B1 in this paper.

Based on the above analysis, index B1 is directly affected by factors such as traffic flow and axle load, and road surface damage such as cracks and cracks are very easy to occur and unevenly distributed. The B1 index in the past 3 years was used to calculate the data fusion inverse cloud algorithm, and due to the relatively limited sample size of this study, the estimation of the inverse parameters was inaccurate, resulting in a low proportion of obscure evaluation of the indicator B1.

V. Conclusion

Based on the methods of hierarchical analysis, G1 method, DEMATEL method and cloud model, this paper realizes the construction of road and bridge health condition assessment model and analyzes the effectiveness and shortcomings of the model.

This paper constructs a road and bridge health assessment index system with five dimensions and 21 indicators, including road facilities, bridge facilities, tunnel facilities, traffic safety facilities and traffic environment. In the DEMATEL results, the five indicators of monitoring and communication facilities, fire fighting facilities, lighting facilities, sight-guiding facilities, and traffic flow have a high degree of centrality and a low degree of cause, which are easy to be affected by fluctuations, and can be used as important indicators of concern for the health status of road and bridge to determine the health status of road and bridge.

The evaluation effect of this paper's health assessment model can make up for the shortcomings of the traditional evaluation of road and bridge health assessment, and through 600 times of fuzzy comprehensive evaluation using the model, the average value of the fuzzy evaluation of each data set is greater than 0.87, the fuzzy evaluation of the proportion of consistency can be with the passage of time and year by year, which verifies the validity of this paper's method. However, at the same time, there are certain errors in the model of this paper, for example, in the case of indicator B1, which is directly affected by factors such as traffic flow and axle loads, cracks, cracks and other pavement damage conditions are very easy to occur and uneven distribution, coupled with the limited number of research samples, which leads to the problem of low fuzzy evaluation of the proportion of consistency. In this regard, this paper proposes the following two improvement ideas:

(1) Under the condition that traffic flow or vehicle axle load data can be obtained, these two indicators or one of them can be given a certain reasonable weight to introduce the fuzzy assessment model evaluation factor set, which will help to reduce the error generated by fuzzy evaluation of B1 indicators on the model.

(2) The kernel density estimation in the non-parametric test method in statistics can be applied to adjust the bandwidth to make the peaks and valleys featured prominently and clearly spaced, to determine the location of the valleys as the boundary value of the new indicator grade interval from the statistical point of view, and to reclassify a more reasonable grade interval of the data of the B1 indicator in order to realize the improvement of the model.

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