Journal of Computer Science and Artificial Intelligence
ISSN: 3078-8242 (Print), ISSN: 3078-2309 (Online) | Vol. 5, No. 1, 2025

Resilience Analysis of Urban Traffic System Based on Extension AHP-CRITIC Comprehensive Weighting-Cloud Model: A Case Study of Guangzhou

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Abstract: Urban traffic congestion has become a common problem faced by major cities around the world. How to improve the resilience of urban transportation systems and alleviate urban traffic congestion issues urgently needs to be addressed. Therefore, taking the resilience of the urban transportation system as the topic, selecting the overall transportation system of Guangzhou as the research object, exploring the resilience of the entire Guangzhou transportation system, and proposing an evaluation model to handle uncertainty and ambiguity. Firstly, by analyzing the resilience of urban transportation and reviewing a large number of relevant literature, a series of indicators for the urban transportation system were selected based on scientific rigor, and an evaluation system for the resilience of the urban transportation system was constructed. Secondly, expert evaluations are collected through questionnaires, and subjective weights are obtained using extensible AHP. The collected objective data is then subjected to CRITIC method to obtain objective weights, which are then combined with game theory for weighting. Finally, a cloud model is introduced to simulate the uncertainty and fuzziness of the evaluation process, calculate the urban resilience index, classify the resilience of Guangzhou's transportation system as "strong resilience", and propose effective suggestions to improve the resilience of Guangzhou's transportation system: enhance social resource investment, create and promote employment, continuously optimize urban construction, develop diversified transportation networks, and finely manage urban cargo flow.

Keywords: Urban transportation system, resilience assessment, extensible AHP-CRITIC combination weighting, game theory, cloud model.

1. Introduction

Urban traffic congestion has become a common problem faced by major cities around the world. With the acceleration of urbanization and the continuous expansion of population size, urban road traffic flow continues to grow, while the growth rate of road infrastructure lags far behind. In addition, the rapid growth of private cars, inadequate public transportation systems, unreasonable urban planning, and imperfect road design have collectively exacerbated the problem of urban traffic congestion. This not only affects people's travel efficiency, but also leads to serious waste, and may even trigger social conflicts and safety issues.

In this context, enhancing the resilience of urban transportation systems has become particularly important. The research on the resilience of urban transportation systems aims to gain a deeper understanding of their operational mechanisms and characteristics, identify key factors that affect system resilience, and propose targeted optimization strategies to improve the overall operational efficiency and stability of urban transportation systems.

By studying the resilience of urban traffic congestion systems, we can identify key factors that affect system operational efficiency and propose targeted improvement measures. This helps to reduce traffic congestion and improve the overall operational efficiency of the urban transportation system [1-4]. The problem of urban traffic congestion not only affects people's travel experience, but also has a negative impact on the environment, economy, and social development of the city. By studying the resilience of urban transportation systems, it can promote the optimization and upgrading of these systems, achieve positive interaction between urban transportation and urban development, and promote sustainable urban development.

Research on the resilience of urban transportation systems can also help improve the city's ability to respond to emergencies such as traffic accidents and adverse weather conditions. By optimizing the structure and function of the urban transportation system, it can quickly restore and maintain normal operation in emergency situations, thereby reducing the losses and impacts caused by such incidents. In addition, research on the resilience of urban traffic congestion systems provides theoretical support and practical guidance for urban traffic planning and management. Through in-depth analysis and research of urban transportation systems, we can propose more scientific and reasonable urban transportation planning and management strategies, providing strong support and guarantee for urban development.

The concept of "resilience" originated in the field of ecology and is used to describe the ability of an ecosystem to maintain its basic structure and function unchanged in the face of external pressures, environmental changes, or disturbances, and even its ability to self adjust and recover. This concept plays a crucial role in understanding the dynamic balance of biological communities and ecosystems. In 1973, Holin first introduced the concept of resilience into academia, defining it as an inherent property of a system, referring to the ability of the population or state variables within the system to maintain their relationships unchanged in the face of continuous changes and various disturbances. Holin's research not only deepens our understanding of ecological resilience, but also provides insights and inspirations for other fields. Due to its significant advantages in addressing the uncertainty of complex systems, resilience has been rapidly adopted and applied by various disciplines such as engineering, economics, and geography. In these fields, resilience is used to describe a system's ability to maintain its structure and function in the face of various challenges, thereby helping people better understand and respond to the dynamic changes of complex systems.

In the fields of urban planning and transportation, the concept of transportation resilience was first proposed by Murray Suite in 2006. The introduction of this concept provides a new perspective and method for the study of urban transportation systems. However, due to the breadth and complexity of the concept of transportation resilience, its definition is not uniform. Different scholars and research institutions often associate resilience with specific abilities of systems or networks, such as "transportation system resilience" and "transportation network resilience," which are often used interchangeably in practical applications without a clear distinction.

2. Research on Urban Traffic Flow Conditions

2.1. The Extensible AHP Method Is Used to Determine Subjective Weights

In order to more accurately understand and apply the concept of traffic resilience, this article chooses to focus on the traffic flow conditions within cities. Traffic flow is an important component of urban transportation systems, directly affecting their efficiency and safety. Therefore, 'traffic resilience' is defined as the ability of urban transportation networks to gradually restore normal operating conditions over time with changes in traffic flow. This ability reflects the adaptability, stability, and recoverability of the transportation network to changes in traffic flow, which is the key to maintaining the structure and function of urban transportation systems in the face of various challenges.

Specifically, transportation resilience includes the following aspects:

(1). Adaptability: In the face of changes in traffic flow, the transportation network can flexibly adjust traffic organization, optimize traffic resource allocation, and adapt to new traffic conditions.

(2). Stability: The transportation network is able to maintain its basic structure and function from being disrupted or impacted, ensuring the stable operation of the transportation system.

(3). Resilience: The ability of a transportation network to quickly restore normal functionality after severe interference or impact, thereby reducing traffic congestion and accidents.

The resilience definition of the transportation system is shown in Table 1.

Table 1. Definition of Resilience of Transportation System

research subject	Definition of Resilience	Related literature
urban transportation system	The system resists, reduces, and absorbs the effects of disturbances to maintain connectivity The level of service received (static resilience), and within a reasonable time and Ability to restore normal and balanced operation within cost (dynamic resilience)	Murray Tate [2]; Wan, et al. [3]; Gonsalves, et al. [4]

To avoid ambiguity in the study area, we define it as an urbanized urban area under relatively closed conditions. In order to more accurately define and explain the concept of urban traffic congestion resilience, inspired by references [5-6], we improved and redrawn the original graph, obtaining the schematic diagram of urban traffic congestion resilience as shown in Figure 1.

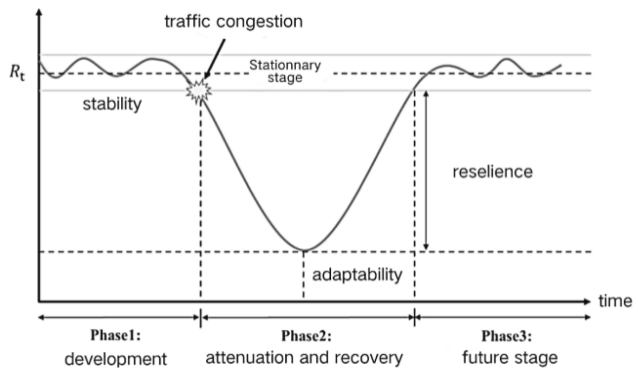

Figure 1. Schematic diagram of urban traffic congestion resilience

In this figure, the black solid line clearly depicts how the urban system is affected by impacts such as floods and other disasters after reaching a stable equilibrium state. This impact significantly reduces the performance of urban systems and is accompanied by functional damage. However, it is worth noting that urban systems do not collapse overnight, but rather gradually recover to pre disaster levels after a period of adaptation and adjustment. This process highlights the resilience and resilience of urban transportation systems in the face of challenges; Tang Shaohu et al. [7] divided the road traffic system into four grids: drainage network, road network, traffic network, and emergency network. Starting from the design of layered grids, they studied the resilience of urban traffic and used the mentioned methods to deduce the changing trends and accurately evaluate the safety resilience of the system; Qiu Baoxing [8] pays special attention to the five core principles of diversity, modularity, high-throughput, demand side management, and intelligence in the transportation of resilient cities, and proposes suggestions for the construction of resilient cities in China based on these five principles; Ma Lingyong et al. [9] used the theory of resilient cities to comprehensively examine the road traffic space system in Daqing City, attaching importance to its risk and vulnerability research. They deeply analyzed the potential risks of the road traffic space system in Daqing City and proposed corresponding resilience improvement strategies.

Many scholars have achieved innovative results in the construction and evaluation of indicators related to the resilience of urban transportation systems. For example, Chen Dan et al. [10] constructed a resilience index system for urban rail transit networks from the aspects of resistance, absorption, and recovery. The three-level indicators include maximum travel time loss rate, removal rate and connection rate, recovery coefficient, combined with passenger flow, passenger travel choices, etc; Liu Juan [11] proposed a resilient city transportation evaluation index system based on the characteristics of urban transportation and the role it plays in resilient cities, from four dimensions: urban comprehensive development resilience, road transportation facility resilience, transportation operation quality resilience, and disaster adaptability resilience; Cutter et al. [12] proposed the Disaster Resilience of Place (DROP) framework, which constructs a measurement index system for disaster resilience from three dimensions: natural systems, social forms, and built environments; Joerin et al. [13] constructed an urban climate disaster resilience evaluation system consisting of 25 indicators from five aspects: economy, system, society, nature, and foundation. In model selection and indicator system evaluation, most scholars adopt methods such as expert scoring, analytic hierarchy process, TOPSIS, fuzzy comprehensive evaluation, etc.

Based on the above literature research, it can be seen that most scholars have certain limitations on the resilience of urban traffic congestion: ① The evaluation methods used are often too single, and there are situations where relying solely on expert scoring methods leads to strong subjectivity or relying solely on data leads to large errors in evaluation results; ②Most studies focus on specific urban transportation roads, lacking comprehensive consideration of the resilience of the overall urban transportation system. Therefore, this article proposes an extended AHP-CRITIC comprehensive weighting cloud model for urban transportation resilience evaluation.

3. Materials and Methods

Table 2. Explanation of urban transportation resilience system indicators

indicator name	Indicator Description
permanent resident population	The permanent population is the main source of urban transportation demand, and its quantity and distribution directly affect the flow and direction of urban transportation
GDP	GDP directly affects the economic foundation and social demand of urban transportation systems
Value added of the tertiary industry	The tertiary industry includes the transportation industry, which will directly promote the development of urban transportation systems
Local general public budget expenditures	The transportation system belongs to the public sector of society and provides guarantees for the operation of urban transportation
Number of motor vehicles owned	The number of motor vehicles will put pressure on the urban transportation system, and when there is enough traffic flow, it will lead to traffic congestion
Employment in transportation	Effective traffic management and maintenance can help alleviate urban traffic congestion
Employment in public facility management	Effectively planning and managing transportation, optimizing public transportation services, can help alleviate traffic congestion
Length of drainage pipeline	It affects the degree of urban waterlogging during rainy days, indirectly affecting urban traffic congestion
Road length	The length of roads provides the supply capacity of the urban system and determines the density and scale of the urban road network
Length of expressway	Highways provide multiple travel options, and their length determines the ability to divert traffic flow between the city and surrounding areas, as well as within the city itself
Road area	Increasing urban traffic capacity and having a larger road area means a larger buffer zone, which promotes driving speed and reduces traffic accidents, helping to alleviate traffic congestion
Pedestrian walkway area	Reasonable planning of urban transportation public areas can help reduce conflicts and interference between pedestrians and motor vehicles.
Per capita urban road area	A larger per capita urban road area means that the city has more road resources to carry traffic flow. This helps alleviate traffic pressure during peak hours and reduce the occurrence of congestion.
Subway operating mileage	Improve people's travel efficiency and alleviate traffic pressure within the city
bridge	Optimize urban transportation layout and network structure, improve traffic mobility and efficiency
Road lighting	Not only does it provide sufficient lighting, but it also provides real-time information on driving instructions and traffic prompts, improving road safety and efficiency, and reducing the possibility of traffic congestion.
freight volume	The volume and speed of trucks occupy more transportation resources and increase the carrying capacity of the road network, exacerbating urban traffic congestion
Port cargo throughput	It will directly affect the freight volume flowing between cities, thereby indirectly affecting urban traffic congestion
Daily average passenger volume of public transportation	Optimizing traffic structure can help reduce the number of vehicles on the road and improve road efficiency
Daily average passenger volume of subway	Optimizing the transportation structure and releasing road resources can help improve people's travel efficiency and alleviate traffic pressure within the city
Equivalent Sound Level of Road Traffic	The level of equivalent sound level in road traffic can indirectly reflect the degree of urban traffic congestion

The urban transportation system is a complex system with multiple factors, and there are many factors that affect its congestion. Based on relevant literature and expert opinions, select the permanent population GDP The urban traffic resilience system is constructed using 21 indicators, including the added value of the tertiary industry, local general public budget expenditures, ownership of motor vehicles, employment in transportation, employment in public facility management, length of drainage pipes, road length, length of highways, road area, sidewalk area, per capita urban road area, subway mileage, bridges, road lighting, freight volume, port cargo throughput, daily average passenger volume of buses, daily average passenger volume of subways, and equivalent sound level of road traffic. The explanations and evaluation systems for each influencing indicator are shown in Table 2 and Figure 5, respectively.

3.1. Determination of Subjective Weights Using Extensible AHP

When evaluating the weights of indicators, it is an advanced approach to use extensible AHP [14] to calculate the subjective weights of evaluation indicators in order to ensure the accuracy and reliability of the evaluation. Compared to AHP, the extensible analytic hierarchy process cleverly introduces the concept of interval numbers, allowing for the construction of reasonable judgment matrices even when there is uncertainty in relative importance. Through this method, we can comprehensively and meticulously evaluate the relative importance between indicators from both the dimensions of randomness and fuzziness. This dual dimensional consideration not only increases the reliability of the evaluation, but also effectively reduces the bias in subjective judgments. Under the framework of the extensible analytic hierarchy process, we can clearly obtain the single ranking weight of the indicator layer elements relative to a certain element in the criterion layer, thereby further determining the subjective weight of each element for the target layer. This systematic analysis method not only provides strong data support for decision-makers, but also helps ensure the objectivity and impartiality of evaluation results.

Based on the constructed rating system, three experts were invited to assign values to the importance of each level of factors using the Sati 9-point scale as a comparison principle through the distribution of questionnaires. The 9-point scale definition is shown in Table 3:

Table 3. point scale and its definition

Scale bij	definition
1	Factor i is equally important as factor j
3	Factor i is slightly more important than factor j
5	Factor i is significantly more important than factor j
7	Factor i is much more important than factor j
9	Factor i is extremely more important than factor j
2,4,6,8	The scale values of the importance of factor i and factor j are between the two adjacent levels mentioned above
Reciprocal of scale value	The inverse comparison between factor i and factor j: bji=1/bij

On this basis, the judgment matrix E is constructed as follows:

$$\mathrm{E} = \left[\begin{matrix} b_{11}\, b_{12} \dots b_{1n} \\ b_{21}\, b_{22} \dots b_{2n} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ b_{n1} b_{n2} \dots b_{nn} \end{matrix} \right] = (\mathrm{b_{ij}})_{\mathrm{n*n}} \tag{1}$$

In order to reduce subjective bias between different indicators, an expansion transformation was introduced and a contraction transformation was used to adjust the values in the matrix. The results of the shrinkage changes are as follows:

$$b'ij = \frac{bij - \min(E)}{\max(E) - \min(E)} = (e_{ij})_{n\times n} \tag{2}$$

Calculate the weights based on the transformed matrix, as shown in the following equation:

$$w_i = \sum_{j=1}^{n}(e_{ij} \Bigg| \sum_{i=1}^{n} e_{ij}) = (w_1, w_2, \cdots, w_n)^T \tag{3}$$

$$w_i \Bigg| \sum_{i=1}^{n} w_i = (w_1, w_2, ..., w_n)^T \tag{4}$$

After calculating the weights, first find the maximum eigenvalue λ max of matrix E, and then perform consistency checks on the judgment matrix. The calculation formula is as follows:

$$\lambda_{max} = \sum_{i=1}^{n}(\sum_{j=1}^{n} e_{ij} w_i / n w_i) \tag{5}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{6}$$

$$CR = \frac{CI}{RI} \tag{7}$$

Among them, the detailed values of RI can be found in the reference When CR<0.1, it indicates that there is no contradiction and the weight result is reliable.

3.2. CRITIC Determines Objective Weights

The CRITIC weighting method analyzes the information content of indicators from the perspectives of comparative strength and conflict. The contrast intensity reflects the differences between evaluation indicators by calculating the mean squared error, while the conflict intensity measures the degree of correlation between indicators by calculating the correlation coefficient. This method comprehensively considers the interrelationships and differences between indicators, making the weight allocation process more objective, reasonable, and scientific.

To avoid affecting the accuracy of the evaluation due to different dimensions, we standardized the indicators as shown in formula (8).

$$x_{ij}^* = \frac{\chi_{ij}}{\sqrt{\sum_{i=1}^{m} \chi_{ij}^2}} \tag{8}$$

Among them, x * ij is the standardized indicator value. When there may be evaluation indicators that are positively (negatively) correlated with the evaluation results in each indicator, it is necessary to perform positive (negative) processing on the indicators as follows:

$$x_{ij} = \frac{x_j^* - x_{max}^*}{x_{max}^* - x_{min}^*} \tag{9}$$

$$x_{ij} = \frac{x_{max}^* - x_j^*}{x_{max}^* - x_{min}^*} \tag{10}$$

The correlation coefficient can reflect the degree of linear correlation. Based on the product of deviations, we measure the degree of correlation between two variables. We believe that the larger the correlation coefficient value of the evaluation indicator, the greater the conflict between the two indicators, reflecting their stronger common ability. Therefore, the weight of the two evaluation indicators is smaller, as shown in formula (11).

$$\zeta_{ij} = \frac{\sum_{i=1}^{\infty}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{\infty}(x_i-\bar{x})^2\sum_{i=1}^{\infty}(y_i-\bar{y})^2}} = \frac{\sum_{i=1}^{\infty}x_i y_i - n\bar{x}\bar{y}}{\sqrt{\left[\sum_{i=1}^{n}x_i^2-n(\bar{x})^2\right]\left[\sum_{i=1}^{n}y_i^2-n(\bar{y})^2\right]}} \tag{11}$$

Among them, Zeta ij (i=1, 2, ..., n; j=1, 2, ..., n) is the correlation coefficient between the i-th indicator and the j-th indicator. The closer Zeta ij is to 1, the greater the correlation between the two indicators. Using the correlation coefficient matrix of evaluation indicators, define the information measurement indicator Cj based on the concepts of contrast intensity and conflict.

$$C_j = \sigma_j \sum_{i=1}^{n}(1-\zeta_{ij}) \tag{12}$$

Among them, σ j is the mean square deviation of indicator j, reflecting the differences between indicators; (1- Zetaij) reflects the conflict between indicators; The larger the Cj value, the greater the amount of information contained. Determine the weight values of the indicators based on the information contained in formula (12), and further calculate the CRITIC indicator weights using the following formula:

$$\overline{w}_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{13}$$

Among them, represents the weight value of indicator j, and the sum of its weights is 1.

3.3. Determination of Combination Weights in Game Theory

The combinatorial weighting method based on game theory is a commonly used method for analyzing game problems. It transforms game problems into combinatorial problems and introduces weights based on combinatorial problems to reflect the interests and strategies of each participant in the game. The core lies in balancing the difference between subjective and objective weights through iteration and adjustment of Lagrange multipliers, in order to obtain a comprehensive set of weights that are both in line with expert opinions and based on data objectivity.

Assuming we have n indicators and introduce Lagrange multipliers, represented by λ, the combination weighting formula is as follows:

$$W_i = \frac{(w_i^{\frac{1}{1+\lambda}})(\overline{w}_i^{\frac{\lambda}{1+\lambda}})}{\sum_{j=1}^{n}(w_j^{\frac{1}{1+\lambda}})(\overline{w}_j^{\frac{\lambda}{1+\lambda}})} \tag{14}$$

Among them, Wi is the combination weighting of the i-th indicator, and the denominator is the weighted sum of all indicators, ensuring that the sum of the combination weights is 1. This formula balances the effects of subjective and objective weights by adjusting the value of λ. When λ approaches 0, it indicates that the combination weight tends to be subjective; When λ approaches ∞, it indicates that the combined weights tend to be objective. Therefore, the determination of the value of λ is crucial, and the most suitable value of λ will be found through iterative optimization. Set an iteration precision of epsion and a maximum iteration count of maxl, and calculate the difference between the current subjective weight and objective weight. The difference calculation method is as follows, using the square of the Euclidean distance.

$$D_i = \sum_{i=1}^{n}(W_i - w_i)^2 + \sum_{i=1}^{n}(W_i - \overline{w}_i)^2 \tag{15}$$

Based on the difference degree Di obtained above, iterate and update the difference degree according to formula (15), and introduce the inspection accuracy as follows:

$$Df = D_{i+1} - D_i, i = 1, 2, \cdots, maxl - 1 \tag{16}$$

Until Df<epsion, it is considered that the optimal combination weight has been found and the iteration is exited. If the maximum number of iterations is reached, it is considered that the optimal combination weight has not been found and the formula needs to be readjusted and optimized.

3.4. Weight Determination Based on Combination Weight Cloud Model

Cloud model is a category of uncertain artificial intelligence in the field of artificial intelligence, originally proposed by Professor Li Deyi, an academician of the Chinese Academy of Engineering, in 1995. It is mainly used for the mutual conversion between qualitative and quantitative methods. The basic concepts of cloud model include "cloud" or "cloud droplet", where "cloud" refers to a branch of it in the domain of discourse, which can be analogized in the form of joint probability (x, μ). Assuming that U is a domain of quantitative numerical representation and C is a qualitative concept in U, if the quantitative value x ∈ U, a random implementation of C is defined as x. If x~N (Ex, En'2) is satisfied, where En ′~N (En, He2), and the membership degree of C satisfies:

$$\mu(x) = \mathrm{e}^{-\frac{(x-Ex)}{(En'2)}} \tag{17}$$

According to the operating mechanism of "cloud", cloud models can be mainly divided into two types of cloud generators - forward cloud generators and reverse cloud generators. The working principles of two types of cloud generators are shown in Figure 2:

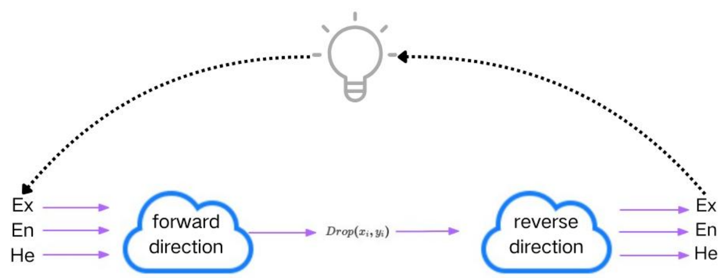

Figure 2. Working principle of cloud generator

There are three main types of reverse cloud algorithms for cloud inverse generators, namely: the reverse cloud algorithm based on first-order absolute center distance (SBCT-1stM), the reverse cloud algorithm based on fourth-order absolute center distance (SBCT-4stm), and the multi-step reverse cloud algorithm (SBCT-SR). This article selects the SBCT-1stM algorithm, which has a higher algorithm complexity compared to others; SBCT-SR has high requirements for data preprocessing and relies heavily on the structure and regularity of the data. The SBCT-1stM algorithm is the first reverse cloud algorithm with no cloud drop certainty, which is efficient, fast, and easy to generalize to high-dimensional applications. The following is the mathematical expression of the SBCT-1stM algorithm.

$$Ex = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{18}$$

$$En = \sqrt{n} * \frac{1}{n\sqrt{2}}\sum_{i=1}^{n} |x_i - Ex| \tag{19}$$

$$He = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(En_i - \overline{En})^2} \tag{20}$$

The method of using forward cloud algorithm to transform the weight cloud model parameters of qualitative concepts into quantitative numerical representations, achieving the transformation from concept space to numerical space. Propose to randomly generate 1500 cloud droplets, which will generate normal random entropy En_i and normal random number x_i for each cloud droplet in the domain space. The calculation formula is as follows:

$$En_i = N(En, He^2) \tag{21}$$

$$x_i = N(Ex, En_i^2) \tag{22}$$

The certainty of cloud droplets is the degree to which cloud droplets can represent qualitative concepts of indicator data, and is the membership degree in the sense of fuzzy sets. The calculation formula is as follows:

$$\mu(x\_i) = e^{\frac{-(x\_i - Ex)^2}{2En\_i^2}} \tag{23}$$

Select the x_i corresponding to the maximum value of the certainty μ (x_i) of the cloud droplet as the final weight of indicator i, that is, the final weight cloud model of each indicator is shown in Figure 3, and normalize the weight values of i indicators to obtain the final weight vector.

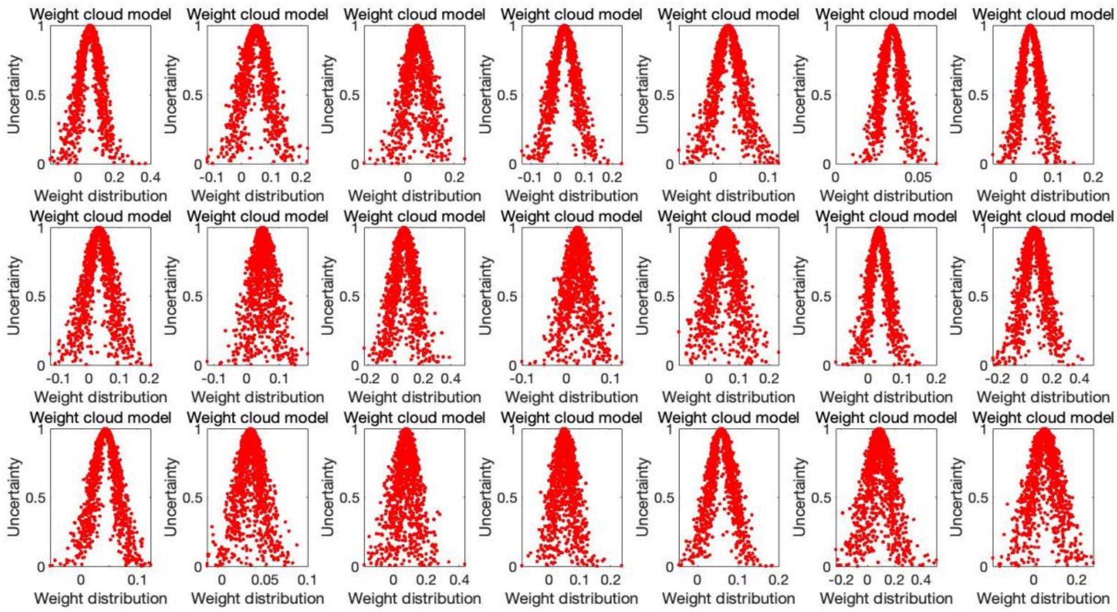

Figure 3. Weighted cloud model

4. Results Solution and Level Classification

The application of the weight calculation method based on the combination weighting cloud model in the evaluation system has demonstrated its unique advantages. It not only deeply combines the subjective insights and wisdom of expert evaluations, but also keenly captures and incorporates the objective facts contained in the evaluation system data. More importantly, based on the solid foundation of combinatorial weighting, this method further refines and enriches the evaluation system's handling of randomness and fuzziness, providing valuable reference and inspiration for qualitative evaluation systems in uncertainty research. This innovative method undoubtedly opens up new ideas and directions for the research and practice of evaluation systems.

After calculating the final weights of each indicator, the objective data is processed using the normalization method, and then the resilience index in terms of resilience, stability, and adaptability is obtained using the comprehensive index method. The calculation formula is as follows:

$$R_i = \sum_{i=1}^{n} W_i^* x_i^* \tag{24}$$

Among them, W * i is the normalized final weight of the i-th indicator calculated based on the combination weighting cloud model, and x * i is the normalized i-th objective data. By combining the weights of the first level indicators from three aspects, the total traffic resilience index of the entire city can be further calculated using the following formula:

$$R = \sum_{i=1}^{3} R_i o w_i \tag{25}$$

Among them, Ri is the resilience index of the i-th aspect, and owi is the CRITIC weight of the i-th aspect for the total traffic resilience index.

In order to evaluate urban transportation resilience more scientifically, this article refers to relevant research results and combines expert opinions to divide urban transportation resilience into four levels, namely V={strong resilience, strong resilience, medium resilience, weak resilience}. The range of different levels of each indicator is determined based on previous research results and statistical yearbooks, and the specific values are shown in Table 4.

Table 4. Grading criteria for resilience evaluation indicators

resilience rating	Level interval	Overview of the situation
resilience	[0.61,1.00)	When the urban transportation network is affected by high traffic flow, it has excellent resilience, stability, and adaptability, and the system can quickly return to normal operation
Strong resilience	[0.40,0.61)	When the urban transportation network is affected by high traffic flow, it has good recovery ability, stability, and adaptability, and the system can be restored to normal operation in a short period of time
Medium resilience	[0.24,0.40)	When the urban transportation network is affected by high traffic flow, its recovery ability, stability, and adaptability are poor, and it takes a certain amount of time for the system to return to normal operation
Low toughness	[0.00,0.24)	When the urban transportation network is affected by high traffic flow, its recovery ability, stability, and adaptability are very poor or very poor. The system needs a long or very long time to recover to normal operation, and may even be unable to recover

5. Empirical Process and Result Analysis

Located in the center of the the Pearl River Delta in southern China, as shown in Figure 4, Guangzhou is the capital city of Guangdong Province and the political, economic, technological, educational and cultural center of the region. It is adjacent to the South China Sea and modern cities such as Hong Kong, Macau, Shenzhen, and Dongguan, jointly forming the prosperous Guangdong Hong Kong Macao Greater Bay Area. Guangzhou has an unparalleled position as a transportation hub, with Guangzhou South Station, one of the world's largest transportation hubs, and Guangzhou Baiyun International Airport, the third largest airport in China, greatly promoting domestic and international connections and trade between Guangzhou and other regions. In addition, Guangzhou has undeniable geographical advantages and abundant resources, providing a solid foundation for the sustainable development of the city. In addition, its profound historical and cultural heritage adds unique charm, attracting numerous tourists. Therefore, choosing Guangzhou as the research object is not only a highly representative case, but also allows for in-depth exploration of its development trajectory, economic model, cultural characteristics, etc., providing rich materials and insights for China's urbanization process.

Figure 4. Geographical location map of guangzhou city

Based on the final weight and objective data, Ri is calculated, and then Ri and owi are used to further calculate the urban traffic elasticity index R, which is 0.4571. According to the classification criteria of the calculated urban elasticity index and elasticity evaluation indicators, the overall transportation system elasticity of Guangzhou is "strong resilience".

From the perspective of resilience, the main factors affecting urban transportation elasticity are permanent population, GDP, and employment in public facility management. The changes in these indicators have a significant impact on resilience, therefore, improving resilience mainly involves addressing these factors. However, although the weights of indicators such as public management fiscal expenditure budget, motor vehicle ownership, and drainage pipe length are relatively low, indicating that their impact on resilience is small, they cannot be ignored.

From a stability perspective, the main factors affecting stability are the length of subway operation, the length of highways, the area of sidewalks, and the length of roads. This highlights the importance of optimizing the internal transportation layout of cities and developing diversified transportation modes. In order to improve traffic elasticity, it is necessary to strengthen the infrastructure of urban transportation, such as increasing the number of highways and sidewalks, and developing diversified transportation routes.

From the perspective of adaptability, the daily average passenger and freight volume of subways and buses are the main factors affecting the adaptability of urban transportation systems. This indicates that developing diversified modes of transportation can increase people's travel choices and alleviate urban traffic pressure. In addition, strict control of freight volume can reduce the number of trucks in the traffic flow, thereby reducing the possibility of traffic congestion.

6. Conclusions

This article takes a broad perspective to study the resilience of the entire transportation system in Guangzhou, and establishes an evaluation system based on the extensible AHP-CRITIC comprehensive weighting cloud model. The model not only combines multiple methods to comprehensively consider evaluation indicators and allocate weights reasonably based on subjective and objective factors, but also introduces the population intelligence of the cloud model, which considers randomness and fuzziness, and better simulates the uncertainty and fuzziness of the entire evaluation process, making the assessment of urban transportation system resilience closer to reality.

References

[1] GONçALVES L A P J, RIBEIRO P J G. Resilience of Urban Transportation Systems: Concept, Characteristics Methods [J]. Journal of Transport Geography, 2020, 85:102727.

[2] Ma Min, Hu Dawei, Shu Lan, et al. Assessment of Resilience and Recovery Strategies for Urban Rail Transit Networks [J]. Journal of Jilin University (Engineering Edition), 2023, 53(02): 396-404.

[3] Ffion G. Dimitris P. The resilience of public transport post-COVID: The case of Great Britain [J]. Case Studies on Transport Policy, 2023, 14.

[4] Tang Shaohu, Zhu Wei, Cheng Guang, et al. Assessment of the Safety Resilience of Urban Road Traffic Systems under Heavy Rain and Waterlogging [J]. Journal of Safety Science and Technology, 2022, 32(07):143-150.

[5] Qiu Baoxing Building Five Guidelines for Resilient Urban Transportation [J]. Urban Development Research, 2017, 24 (11): 1-8+149.

[6] Ma Lingyong, Wang Zhenhao, Liang Jing, et al. Research on the Resilience Strategy of Road Traffic Space in Daqing City Based on the Resilience City Theory [J]. Henan Science, 2018, 36 (06): 978-984.

[7] Chen Dan, Zhong Yugang, Li Xuanrui, et al. Construction and Comprehensive Evaluation of Resilience Index System for Urban Rail Transit System [J/OL]. Journal of Wuhan University of Technology (Transportation Science and Engineering Edition): 1-14 [2024-05-07].

[8] Liu Juan Research on the Construction and Improvement Strategies of Resilient Urban Transportation Evaluation Index System [C]//Academic Committee on Urban Transportation Planning of China Urban Planning Society Green, Smart, and Integrated: Proceedings of the 2021/2022 China Urban Transportation Planning Annual Conference [Publisher unknown], 2022: 7.

[9] CUTTER S L, BARNES L, BERRY M, et al. A placebased model for understanding community resilience to natural disasters [J]. Global Environmental Change, 2008, 18(4): 598-606.

[10] JOERI J, SHAW R, TAKEUCHI Y, et al. The adoption of a climate disaster resilience index in Chennai, India [J]. Disasters, 2014, 38(3): 540-561.

[11] MENG Z, ZHANG J, HU Y, et al. Temporal prediction of landslide-generated waves using a theoretical-statistical combined method [J]. J Mar Sci Eng, 2023(11): 1151.

[12] Fu Zhigang, Wang Tao, Kong Linghao, et al. Assessment of Electricity Consumption Status of Important Power Customers Based on AHP-TOPSIS Algorithm [J]. Grid Technology, 2022, 46 (10): 4095-4101.

[13] Li Deyi, Meng Haijun, Shi Xuemei Subordinate Cloud and Subordinate Cloud Generator [J]. Computer Research and Development, 1995 (06): 15-20.

[14] Liu Changyu, Feng Mang, Dai Xiaojun, et al. A New Reverse Cloud Algorithm Based on Cloud X Information [J]. Journal of System Simulation, 2004, 16 (11): 2417-2420.