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Key corridor identification in multi-objective highway networks based on feature lines

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A B S T R A C T

To enhance the overall accessibility and operational efficiency of highway networks, this paper proposes an integrated analytical approach based on node importance, network reliability, and critical link identification to identify key transportation corridors within highway networks. Initially, a comprehensive node importance measurement method is developed by integrating static geometric characteristics and dynamic traffic attributes of complex networks. The weights of static indicators are calculated using an improved entropy weight method, while the dynamic importance of nodes is assessed based on the h-index, resulting in a ranked node importance list. Subsequently, from the perspective of network reliability, critical nodes are identified and ranked by simulating node failure scenarios through attack strategies, evaluating their impact on network connectivity and travel time. Further, critical links are identified utilizing the Stochastic User Equilibrium (SUE) model and Ant Colony Optimization (ACO). Finally, a multi-objective key corridor identification method based on feature lines is formulated by comprehensively considering node importance, network reliability, and critical road segments. An empirical analysis is conducted on the highway network across 11 counties/districts of Zhaotong City, Yunnan Province. Three key transportation corridors are ultimately identified:Ludian County-Zhaoyang District-Daguan County-Yanjin County, Ludian County-Zhaoyang District-Daguan County-Yongshan County, Ludian County-Zhaoyang District-Yiliang County.

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1. Introduction

Highway networks, serving as the backbone of China's transportation system, play a pivotal role in national economic development and regional integration. With rapid socio-economic growth, traffic volumes and transport demands on highways continue to surge, leading to an expansion of the network scale. However, this rapid development has simultaneously brought numerous challenges, including sharp increases in traffic flow, frequent traffic accidents, and relatively lagging network planning and management capabilities. These factors collectively impair the accessibility and operational reliability of highways.In recent years, driven by a significant rise in motor vehicle ownership, China's highway networks have faced unprecedented transport pressure. Highways undertake the vast majority of the nation's passenger and freight transport tasks, where their accessibility and reliability are directly linked to the stable operation of the national economy and regional development. Nevertheless, failures or congestion at critical nodes or critical links within the highway network can substantially degrade the overall network efficiency, potentially triggering regional traffic disruptions. Therefore, identifying and optimizing key transportation corridors within highway networks-ensuring their stability and efficiency-is of paramount importance for enhancing the comprehensive transport capacity of national and regional transportation systems.

Currently, substantial progress has been made in transportation corridor research. Regarding transportation corridor identification, Vilain and Wolfrom (2000) analyzed key intersections connecting New Jersey and New York City, investigating the overlap of passenger and freight traffic during peak hours, and proposed a peak-hour corridor identification method. Takebayashi (2007) examined the spatial-temporal concentration patterns of various vehicle types on roads around Tokyo,

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Japan, identifying major transportation corridors. Wu et al. (2015) introduced the Ant Colony Optimization (ACO) algorithm and an equilibrium model to achieve quantitative identification of transportation corridors. Wang et al. (2022) incorporated complex network theory to improve the node importance model, integrating network topological characteristics and positional attributes to propose an optimization method for corridor layout identification.

In transportation corridor identification, scientifically and rationally assessing the importance of nodes within the transportation network is crucial. Yuan et al. (2023) proposed "hyperedge selection degree" to measure the importance of hub nodes. Kopsidas and Kepaptsoglou (2022) developed a novel node importance evaluation model based on closeness centrality, weighted node degree, and betweenness centrality. Similarly, Chen et al. (2019) applied these metrics to evaluate node importance in Chongqing's transportation network. Meng et al. (2020) employed principal component analysis (PCA) and factor analysis to construct a comprehensive importance model for assessing nodes in Shenzhen's transportation network. Ma et al. (2020) comprehensively considered network vulnerability and passenger flow demand, constructing a node importance model based on passenger flow loss rate to identify network weak points.

Network reliability measures the robustness and sustained operational capability of transportation networks when facing disruptions. In transportation corridor identification, network reliability analysis aids in identifying corridors that maintain high service levels even under network failure conditions. The seminal work by Iida and Wakabayashi (1989) laid the foundation in this field; they explored changes in overall connectivity under partial network failures, providing theoretical support for subsequent network reliability research. Subsequently, Barahimi et al. (2022) investigated how to compute travel time reliability in urban transportation networks while accounting for correlations among links along paths. Li et al. (2023) utilized complex network theory to analyze the reliability of the land transportation network in the Guanzhong Plain urban agglomeration. Their results demonstrated that a multi-subnet structure exhibits greater reliability against both intentional and random attacks. Dong et al. (2023) studied the resilience of transportation networks under flood disturbances by evaluating link reliability and stability, proposing a novel network resilience metric based on link quality thresholds.

Furthermore, in the context of key corridor identification, several scholars have specifically investigated critical links within road networks. Patil and Bhavathrathan (2020) studied the identification of critical links under changes in network capacity. Jana et al. (2023) utilized an edge-based Graph Neural Network (GNN) to rapidly identify critical links, aiding planners and emergency managers in making more effective decisions during both conventional operations and disaster periods. Henke et al. (2024) analyzed the vulnerability of road networks to external shocks through accessibility and link importance indicators, identifying critical roads for emergency scenarios. Li and Luo (2018) developed a critical link identification model for scenarios involving multiple link failures. Su et al. (2017) constructed a spatiotemporal correlation model and proposed a link importance measurement model based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to identify critical links. Li et al. (2020) employed a binary logit model to proactively search for critical links based on travel time impact.

Current research has achieved significant progress in transportation corridor identification, node importance evaluation, and Critical Link identification. By synthesizing domestic and international research trends, the following observations emerge:

(1) Studies on node importance predominantly rely on static models, lacking dynamic analysis of node importance and in-depth exploration of its interrelationships with other complex transportation network elements.

(2) Existing research on network reliability primarily focuses on theoretical analyses of single metrics, exhibiting relatively weak systematic investigation—particularly regarding the coordination and integration of diverse reliability indicators. Moreover, the potential of network reliability in practical transportation planning applications has not been sufficiently emphasized.

(3) Regarding Transportation Corridor Identification, research mainly concentrates on identifying Key Corridors but seldom explores their interactive relationships with critical network features such as critical nodes and Critical Links. Concurrently, existing studies often neglect temporal dimensions: Key Corridors may evolve across different development stages of transportation networks. Consequently, current Key Corridor identification methods lack consideration of temporal factors, resulting in weak dynamic adaptability of outcomes.

Based on this, this paper proposes an integrated analytical approach that combines the static geometric characteristics and dynamic traffic attributes of complex networks to accurately measure node importance within highway networks. An improved entropy weight method is employed to assign weights to static geometric indicators, while dynamic analysis based on the h-index comprehensively assesses the criticality of nodes in the network.Building upon this foundation, the study further incorporates connectivity reliability and travel time reliability from a network reliability perspective to identify and optimize critical nodes and links significantly impacting overall transportation corridors. Critical links are identified and validated using the Stochastic User Equilibrium (SUE) model and Ant Colony Optimization (ACO).Finally, a multi-objective key corridor identification method based on feature lines is developed by integrating three datasets: node importance rankings, critical node identification results, and critical link identification outcomes. The proposed method is empirically validated through a case study.

2. Model formulation

2.1 Node importance measurement considering static and dynamic characteristics of complex highway networks

Against the backdrop of complex networks, node importance directly influences network connectivity, traffic flow assignment, and overall system stability. To comprehensively measure the role of nodes within highway networks, this paper proposes a node importance assessment model that integrates static geometric characteristics and dynamic traffic attributes. This approach aims to achieve a precise assessment of node criticality through a synergistic analysis of their static and dynamic properties.

2.1.1 Static analysis

In the static analysis, degree, closeness centrality, betweenness centrality, eigenvector centrality, and clustering coefficient are selected as key static indicators. An improved entropy weight method - which modifies the traditional entropy weight approach to reduce computational errors when entropy values equal 1 - is applied to calculate node importance under static geometric characteristics. The static geometric feature-based node importance model is established as follows:

$$Z_i = \sum \alpha_j \frac{r_{ij}}{r_{jave}} \times 100\% \tag{1}$$

In Eq. (1): Z_i denotes the node importance of node i, where a higher value of Z_i indicates greater importance of node i; α_j represents the weight of the j-th indicator; r_{ij} is the value of the j-th indicator for node i; r_{jave} denotes the average value of the j-th indicator across all nodes within the region.

2.1.2 Dynamic analysis

In dynamic analysis, node importance measurement incorporates the mutual influences of traffic flows between nodes and their spatial correlations. This study employs the h-index to evaluate node importance within dynamic traffic environments. Originally used to quantify academic influence of researchers, the h-index is adapted here to measure node significance in traffic flows (Huang et al., 2022) The Annual Average Daily Traffic (AADT) is adopted to characterize dynamic attributes of nodes, combined with analysis of traffic flow correlation coefficients between nodes. Node traffic flow is calculated as follows:

$$Q_i = \sum_{a \in J(i)} f^a(i,a) \tag{2}$$

In Eq.(2): Q_i denotes the generated and attracted traffic volume at node i; a represents the a-th node connected to node i, where a=1,2,3…， m; $J(i)$ is the set of nodes adjacent to node i; $f^a(i,a)$ denotes the Annual Average Daily Traffic (AADT) on the link between node i and its adjacent node a.

The correlation coefficient between nodes, computed via the Pearson correlation coefficient, reflects the traffic flow interdependence. The correlation coefficient matrix $R(X)$ is computed as follows:

$$\gamma_{ij} = \frac{\sum_{t=1}^{N}(X_{it} - \overline{X}_i)(X_{jt} - \overline{X}_j)}{\sqrt{\sum_{t=1}^{N}(X_{it} - \overline{X}_i)^2} \cdot \sqrt{\sum_{t=1}^{N}(X_{jt} - \overline{X}_j)^2}} \tag{3}$$

$$R(X) = (\gamma_{ij})_{m \times m} \tag{4}$$

In Eqs. (3) and (4): γ_{ij} denotes the correlation coefficient between node i and node j; X_{it} and X_{jt} represent the traffic flow at node i and node j at time t, respectively; $\overline{X}_i$ and $\overline{X}_j$ denote the average traffic flow at node i and node j, respectively; N indicates the number of observations in the time series.

After calculating the correlation coefficient matrix of the highway network nodes, values are assigned to the correlation coefficients to derive the node attraction coefficients and the node attraction coefficient matrix H for highway nodes:

$$h_{ij} = \left[(\gamma_{ij} - \min \gamma_{ij}) \div \frac{1 - \min \gamma_{ij}}{m} \right] \tag{5}$$

$$H = \left(h_{ij} \right)_{m \times m} \tag{6}$$

In Eqs. (5) and (6): h_{ij} denotes the node attraction coefficient between node i and node j; [ ] represents rounding to the

nearest integer (e.g., [2.2] = 2, [1.7] = 2); Matrix H indicates the attraction frequency of nodes.

By constructing the node attraction coefficient matrix H and calculating the h_i -index of nodes based on this matrix, node importance within the dynamic network is quantified as follows:

$$h_i = \max(k) : c_k^i \geq k \tag{7}$$

In Eq. (7): $c_k^i (1 \leq k \leq m)$ denotes the node attraction coefficient of the k -th node (arranged in descending order) toward node i.

2.1.3 Node importance analysis integrating static geometric characteristics and dynamic traffic attributes

Static geometric characteristics analysis focuses on the topological recognition of the network, while dynamic traffic attributes emphasize the volatility and correlations of traffic flows. To comprehensively evaluate node importance, this study integrates both modeling approaches, ultimately ranking nodes by calculating the intersection degree and intersection rank value.

(1)Intersection degree

Let top_k^u denote the sequence set comprising the top k nodes ranked in descending order of node importance under the u -th model (where Model 1 ($u=1$) employs static geometric characteristics, and Model 2 ($u=2$) employs dynamic traffic attributes). The intersection degree between two ranked sequences $A(u=1)$ and $B(u=2)$ is defined as:

$$S(X,Y,k) = \frac{se(A \bigcap B)}{k} = \frac{se(top_k^1 \bigcap top_k^2)}{k} \tag{8}$$

In Eq.(8): $se(A \bigcap B)$ denotes the number of elements in set $A \bigcap B$. A higher intersection degree indicates greater consistency between the two ranked sequences. Hence, nodes exhibiting highly consistent rankings from both models retain their original positions in the final sequence.

(2) Intersection rank value

Let $ord_{u\ 1 \leq v \leq k}^v$ represent the rank value of the v -th node in sequence top_k^u. The intersection rank values for sequences A and B under their intersection are defined as:

$$Sort_u^k \mid (A \bigcap B) = \frac{\sum_{v \subset X \bigcap Y} ord_u^v}{se(A \bigcap B)} \tag{9}$$

The difference between the two *Sort* values is $\Delta Sort(1,2,k) = Sort_1^k - Sort_2^k$. If $\Delta Sort(1,2,k) < 0$, the node importance calculated by Model 1 is higher than that by Model 2. Consequently, for nodes with significant ranking discrepancies, the final ordering prioritizes results from Model 1.

2.2 Critical node identification based on network reliability

Network reliability refers to the ability of a transportation network to maintain normal operation under various disruptions. As vital connection hubs, critical nodes serve as core components ensuring network stability. Once these nodes fail or are attacked, they significantly impact the overall connectivity and operational efficiency of the network. Identifying critical nodes facilitates the development of more effective traffic management strategies and enhances the network's resilience. To quantitatively evaluate network reliability, this study comprehensively considers connectivity reliability and travel time reliability metrics to identify critical nodes.

2.2.1 Network reliability evaluation metrics

(1) Connectivity reliability

Connectivity reliability measures the probability that nodes remain reachable within the network—i.e., the network's capacity to maintain connectivity when certain nodes or paths fail. Here, the metrics selected are the relative size of the largest connected subgraph and network efficiency, supplemented by topological potential analysis to quantify connectivity reliability.

The relative size of the largest connected subgraph (S) measures the proportion of the largest remaining connected subgraph

after node or link failures, effectively capturing the structural robustness of the network:

$$S = \frac{n'}{n} \tag{10}$$

In Eq. (10): n' denotes the number of nodes in the largest connected subgraph within the network; n represents the total number of nodes in the original network.

The global network efficiency (E), serving as a measure of the network's overall operational efficiency, evaluates changes in the average shortest path length between nodes when partial network failures occur, thus reflecting the extent of performance degradation across the network:

$$E = \frac{2}{n(n-1)} \sum_{i \geq j}^{n} \frac{1}{d_{ij}} = \frac{2}{n(n-1)} \sum_{i \geq j}^{n} \varepsilon_{ij} \tag{11}$$

In Eq. (11): d_{ij} denotes the shortest path length between nodes i and j; ε_{ij} represents the efficiency between nodes i and j, defined as the reciprocal of d_{ij} .The global network efficiency ratio (η) is derived from the ratio of the network-wide efficiency E_i after node removal to the initial network-wide efficiency E_o, expressed as:

$$\eta = E_i / E_o \tag{12}$$

Topological potential, as an indicator for evaluating node importance, reveals the network structure's sensitivity to local node failures. Comprehensively considering two intrinsic metrics—the relative size of the largest connected subgraph and the global network efficiency ratio after node attacks—the topological potential φ_{v_i} of any node v_i in the network can be expressed as (Su et al., 2010):

$$\varphi_{v_i} = \sum_{j=1}^{n} \left[\left(m_{j1} + m_{j2} \right) \times e^{-\left(\frac{d_{ij}}{\sigma} \right)^2} \right] \tag{13}$$

In Eq. (13): σ denotes the influence factor, representing the impact scope of each node; m_{j1} and m_{j2} represent the mass of node $v_j \left(j = 1, 2, \ldots, n \right)$, indicating two distinct attributes of each node.To further optimize the influence factor σ, the concept of potential entropy is introduced to quantify the distribution uniformity of node importance across the network. Let $\varphi(v_1), \varphi(v_2), \ldots, \varphi(v_n)$ be the topological potential value of node $v_1, v_2, \ldots, v_n$, then the potential entropy is defined as:

$$\mathrm{H} = -\sum_{i=1}^{n} \frac{\varphi(v_i)}{Z} \log\left(\frac{\varphi(v_i)}{Z} \right) \tag{14}$$

In Eq. (14): $Z = \sum_{i=1}^{n} \varphi(v_i)$ denotes the normalization factor for topological potential. The influence factor value σ that minimizes the potential entropy is selected, corresponding to the least uniform distribution of node importance and minimal network uncertainty, thereby enabling topological potential computation. A higher topological potential indicates greater criticality of the node within the network; conversely, a lower value implies reduced node significance.

(2) Travel time reliability

Travel time reliability focuses on the network's ability to maintain journey times within acceptable ranges under varying traffic conditions—i.e., the probability that travelers reach destinations within expected timeframes. It is defined as the probability that travel time does not exceed a specific threshold at a given confidence level:

$$P_a = P\left(T_a \leq t_a \right) = \phi\left[\frac{t_{a0} - E\left(T_a \right)}{\sqrt{\mathrm{var}\left(T_a \right)}} \right] \tag{15}$$

In Eq. (15): P_a denotes the reliability of the road segment a; T_a represents the actual travel time on segment a; t_a indicates the acceptable threshold; $\phi(\cdot)$ is the standard normal distribution function; t_{a0} denotes the free-flow travel time of the segment. Based on the BPR function, the segment travel time is assumed to follow a normal distribution, yielding expectation $E(T_a)$ and variance $\mathrm{var}(T_a)$.

2.2.2 Critical node identification based on network reliability impacts

Building upon the established network reliability metrics, this section proposes a reliability quantification method based on node importance ranking. First, leveraging the node importance ranking framework, a node attack model is constructed to simulate potential network damage scenarios through sequential removal of critical nodes. This process analyzes reliability variations under different damage levels, comprising two components:(1)Connectivity reliability analysis: Quantifies structural robustness by computing changes in the relative size of the largest connected subgraph and network efficiency ratio under attack scenarios, ultimately deriving each node's topological potential.(2)Travel time reliability Analysis: Employs the node contraction method to evaluate changes in travel time reliability after node/path failures, revealing the network's dynamic adaptability in real-world operations. Based on computed topological potential and travel time reliability values post-attack, the criticality index of nodes is calculated using the following formula:

$$I_i = \frac{\varphi_{v_i}}{Z} + \left(1 - \frac{E_i(G)}{Z_1}\right) \tag{16}$$

In Eq. (16): I_i denotes the criticality index of node i; φ_{v_i} represents the topological potential of node i under attack; $E_i(G)$ indicates the comprehensive travel time reliability of the network when node i is attacked; $Z_1 = \sum_{i=1}^{n} E_i(G)$ is the normalization factor for the network-wide comprehensive travel time reliability.

2.3 Critical segment identification based on traffic volume

In transportation network research, identifying critical segments is pivotal for enhancing network efficiency and reliability. This section adopts a Stochastic User Equilibrium (SUE) model from a highway traffic volume perspective to identify critical segments, with path optimization achieved through Ant Colony Optimization (ACO).

2.3.1 Stochastic user equilibrium model

The SUE model is a network assignment method based on stochastic principles, simulating users' route choice behavior under uncertain conditions. This model enables preliminary identification of high-load segments (i.e., critical segments) in stochastic environments. Its core mechanism utilizes a probability assignment matrix to randomly distribute travel demand across feasible paths, subsequently analyzing path load conditions (Zhou, 2022). Path selection probability is computed based on the path's impedance function:

$$P_k^{rs} = \frac{e^{\frac{-\theta c_k^{rs}}{\bar{c}^{rs}}}}{\sum_{q=1}^{m} e^{\frac{-\theta c_q^{rs}}{\bar{c}^{rs}}}} \tag{17}$$

In Eq. (17): P_k^{rs} denotes the probability of selecting the k-th path between origin-destination (OD) pair r-s; c_k^{rs} represents the impedance of the L-th path for OD pair r-s; $\bar{c}^{rs}$ indicates the average travel impedance across all paths between OD pair r-s; m is the total number of paths between OD pair r-s; θ denotes the dispersion parameter. Through this model, segments experiencing high stochastic loads can be identified.

2.3.2 Ant Colony Optimization

After preliminary identification of critical segments, Ant Colony Optimization (ACO) is employed to further refine path selection. ACO is a bio-inspired optimization algorithm mimicking natural ant foraging behavior, particularly effective for solving optimal path problems in complex networks (Wu and Huang,2015). Its core principle utilizes a pheromone-based positive feedback mechanism to guide artificial ants toward optimal paths in the search space, achieving global optima. In critical segment identification, ACO contributes through:(1)Global Path Optimization: Identifying segments sustaining high loads even under system optimal conditions;(2)Adaptive Pheromone Adjustment: Dynamically updating pheromones to adapt to traffic flow variations, enhancing identification accuracy.The path selection process in ACO is defined as follows:

$$U_{ij} = \frac{\theta_{ij}^{d}\left(\eta^{d}{}_{ij}\right)^{\alpha} + \theta_{ij}^{t}\left(\eta^{t}{}_{ij}\right)^{\beta}}{\sum_{j=1}^{J(i)}\left(\theta_{ij}^{d}\left(\eta^{d}{}_{ij}\right)^{\alpha} + \theta_{ij}^{t}\left(\eta^{t}{}_{ij}\right)^{\beta}\right)} \quad \left(j \in J(i)\right) \tag{18}$$

In Eq. (18): U_{ij} denotes the probability of travelers moving from node i to node j; θ_{ij}^{d} and θ_{ij}^{t} represent the pheromone concentration on the path from node i to node j; α and β are the weight coefficients for pheromone and visibility; η is the heuristic factor, defined as the reciprocal of travel distance.Through iterative computation, the algorithm dynamically updates pheromone concentrations to guide path selection flows, ultimately identifying critical segments that sustain high loads under system optimal conditions.

3. Identification of critical transport corridors in highway networks under multi-objective framework

Critical transport corridors are defined as vital passages composed of interconnected transport paths linking major node cities, which concentrate substantial passenger/freight demand and transportation resources. While existing critical segment identification methods rely exclusively on traffic volume—exposing theoretical limitations—the actual formation and operation of corridors are governed by a triad of interdependent factors: the economic significance of node cities, traffic load intensity, and network reliability. Disruptions to these corridors may trigger cascading failures, drastically degrading network-wide operational efficiency and potentially causing severe regional economic consequences. To address these limitations, this study develops an integrated methodological framework synthesizing three objectives: node importance (structural centrality), Critical Nodes (reliability-impacted hubs), and Critical Segments (high-load pathways). Guided by OD demand clustering analysis, the identification process employs OD Projection Modeling to quantify transport lines' attraction to origin-destination flows. Crucially, we innovatively introduce node importance and reliability-adjusted critical nodes to dynamically correct two key parameters: node connection attraction (reflecting demand gravitation) and residual flow capacity (measuring congestion resilience). This dual-correction mechanism transcends single-metric approaches by capturing the dynamic equilibrium between traffic attraction and network robustness. Furthermore, Characteristic Line Analysis visualizes spatial distribution and flow patterns, transforming abstract OD clusters into geospatial corridors with quantifiable traffic concentration axes, bottleneck segments, and alternative routing potentials. The full methodology—systematically addressing theoretical gaps through multidimensional integration of topological significance, reliability impacts, and spatial-flow dynamics-is depicted in Fig.1, providing a comprehensive toolset for infrastructure resilience planning.

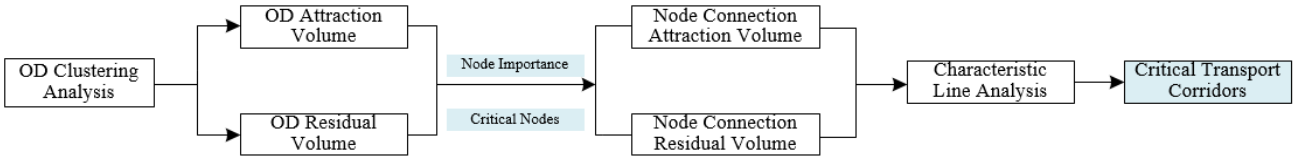

Fig. 1. Identification of critical transport corridors based on OD clustering analysis

3.1 Determination of characteristic lines based on OD clustering analysis

To simulate the attraction effect of transport lines on OD demand, this study first establishes an OD Projection Model. This model conceptualizes connections between node cities as transport lines (where critical transport corridors comprise multiple such lines), quantifying the attraction effect through the following expression:

$$E = \left(1 - \frac{h}{r}\right)^2 \tag{19}$$

In Eq. (19): E denotes the attraction effect of a transport line on OD demand; r represents the attraction radius of the transport line; h indicates the distance ($0 \le h \le r$) between the OD line and the node connection. For a given attraction radius r of a node connection, the attraction effect weakens as distance h increases.

By projecting all OD lines onto node city connections, the OD attraction volume and residual flow capacity of node connections can be preliminarily calculated.However, relying solely on OD demand distribution may inadequately reflect real-world network conditions. Therefore, this study further incorporates node importance and network reliability to correct both attraction volume and residual capacity. The corrected values are computed as follows:

Node Connection Attraction Volume：

$$a_{ij} = \tau_{ij}\delta_{ij}od_{ij}\left(1-\frac{h_{ij}}{r}\right)^2 \tag{20}$$

Node Connection Residual Capacity：

$$b_{ij} = \tau_{ij}\delta_{ij}od_{ij}\left(1-\left(1-\frac{h_{ij}}{r}\right)^2\right) \tag{21}$$

In Eq. (20) and Eq. (21): a_{ij} denotes the attraction volume of the connection between nodes i and j; τ_{ij} represents the product of the importance values of nodes i and j; δ_{ij} indicates the product of the importance values of nodes i and j under the influence of network reliability; od_{ij} is the OD demand volume between nodes i and j; h_{ij} denotes the projection length of the connection between nodes i and j onto the horizontal reference line.

After OD projection, node connections exhibit a clustered distribution, with high-traffic-density connections serving as potential characteristic lines for critical transport corridors. Within the same cluster, different characteristic lines primarily derive their attraction volume from identical OD lines, whereas across distinct clusters, attraction volumes originate predominantly from different OD lines. To quantify correlations between characteristic lines, this study introduces the influence coefficient:

$$f_{12} = 1-\frac{Residual\ Attraction\ of\ C_2\ \ after\ \ C_1}{C_2\,Attraction\ Volume} \tag{22}$$

In Eq. (22): Residual Attraction of C_2 after C_1 refers to the attraction volume of characteristic line C_2 to the residual OD demand after characteristic line C_1 has absorbed primary demand. Analogously, other influence coefficients can be derived. Assuming K characteristic lines are obtained through OD projection, an influence matrix $F=\left(f_{ij}\right)_{K\times K}$ is constructed. By developing a thresholded influence matrix F, this framework quantifies the influence intensity of each characteristic line on others. Subsequently, λ-matrix thresholding processing is applied to matrix L to identify strongly correlated bundles of characteristic lines. Ultimately, within each bundle, the characteristic line exhibiting the maximum sum of influence coefficients is selected as the representative feature line for critical transport corridors.

3.2 Identification of critical transport corridors

Leveraging the influence coefficient matrix, this study employs a fuzzy clustering algorithm to classify highway segments through a multi-stage analytical process. First, the influence coefficient matrix undergoes standardization via max-normalization to ensure dimensional consistency. Subsequently, a fuzzy similarity matrix is constructed using the max-min method, followed by computation of the transitive closure through iterative squared method applications. By dynamically adjusting the threshold matrix size, segments exhibiting similar characteristics are systematically clustered, generating a dynamic clustering dendrogram that visualizes hierarchical relationships. Building upon these results, the clustering outcomes are refined by integrating critical segments and their corresponding traffic volumes identified in Section 1.3, ensuring alignment with empirical load patterns.These critical segments are synthesized into critical transport corridors based on their connectivity. Critical transport corridors may be formed either by critical segments connecting two node cities directly, or by concatenating critical segments linking multiple cities. Through geospatial connectivity analysis, relevant segments are consolidated to identify the resulting critical transport corridors.

4. Case study

This research selects Zhaotong City, Yunnan Province as the study area, focusing on its expressway network (including completed, under construction, and planned expressways). Based on November 2021 traffic flow data, the analysis centers on transportation nodes across 11 districts/counties of Zhaotong City. Preliminary work involved data preprocessing and statistical analysis of traffic volumes for all expressway segments. Using these data, the four-step forecasting model projected 2030 transportation demand to generate an OD matrix. The predicted traffic volumes were then allocated to specific road segments through the multipath probability assignment method, ultimately producing a traffic assignment diagram to provide the basis for subsequent research.

4.1 Node importance calculation

This study focuses on the expressway network coverage area of Zhaotong City, constructing a road network topological structure diagram by mapping county centroids to nodes and expressway segments to edges to evaluate node importance. The network comprises 11 nodes, as illustrated in Fig.2.

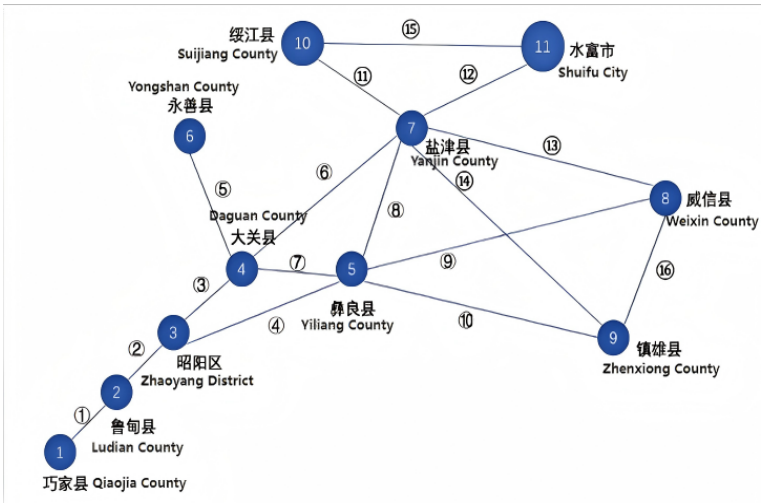

Fig.2. Road network topological structure diagram

In the static analysis, utilizing November 2021 data from Zhaotong City's expressway network, we computed network node-layer eigenvalues through Matlab programming and Gephi software. Using a modified entropy weight method, the weights for degree, closeness centrality, betweenness centrality, eigenvector centrality, and clustering coefficient were determined as 0.25, 0.24, 0.24, 0.11, and 0.16 respectively. According to Eq. (1), node importance under static geometric characteristics was calculated (Table 1). Yanjin County (1.751), Daguan County (1.457), Zhaoyang District (1.385), and Yiliang County (1.545) ranked highest in node importance.

In the dynamic analysis, based on 30-day traffic flow data from November 2021, we computed the traffic flow correlation coefficients between nodes and the node attraction coefficient matrix, with nodes subsequently ranked via the h-index to yield the following results:

(1)Correlation coefficient matrix

The traffic flow correlation coefficients between expressway segments were computed using Eqs. (3) and (4), constructing the sample correlation coefficient matrix $R_{\mathrm{m\times m}}(X)$ as follows:

$$R=\begin{bmatrix} 1 & 0.0903 & \cdots & 0.3091 \\ 0.0903 & 1 & \cdots & -0.2096 \\ \vdots & \vdots & \ddots & \vdots \\ 0.3091 & -0.2096 & \cdots & 1 \end{bmatrix}_{11\times 11}$$

(2) Node attraction coefficient matrix

The node attraction coefficients between all node pairs were calculated using Eq. (5), resulting in the node attraction coefficient matrix $H_{\mathrm{m\times m}}(X)$ as follows:

$$H=\begin{bmatrix} 11 & 4 & \cdots & 6 \\ 4 & 11 & \cdots & 2 \\ \vdots & \vdots & \ddots & \vdots \\ 6 & 2 & \cdots & 11 \end{bmatrix}_{11\times 11}$$

(3)*h*-index

After obtaining the node attraction coefficient matrix of the road network nodes, the attraction coefficients from all nodes to node i were sorted in descending order. When conditions $c_k^i \geq k$ and $c_{k+1}^i < k+1$ are satisfied, the *h*-index of node i is determined (see Table 1).

In evaluating road network node importance, both static and dynamic factors constitute indispensable key variables. Consequently, nodes exhibiting higher intersection degree between these two factor categories and achieving top rankings are selected as critical nodes. By comparing node importance rankings derived from both algorithms and utilizing the intersection sort value (where conditions $Sort_1^{11} \mid (top_1^{11}, top_2^{11}) = 1.97$ and $Sort_2^{11} \mid (top_1^{11}, top_2^{11}) = 2.45$ are satisfied with difference $\Delta Sort(1,2,11) = Sort_1^{11} - Sort_2^{11} = -0.48 < 0$), we infer that nodes identified through the h-index-based dynamic traffic algorithm demonstrate superior importance. Therefore, the final ranking prioritizes results from the dynamic traffic algorithm, while within the same rank tier, static geometric rankings further differentiate nodes. The ultimate node importance rankings are presented in Table 1.

Table 1
Node importance and ranking of counties (districts) in Zhaotong City

Node	Node importance	Rank	*h*-index	Rank	Comprehensive rank
1	0.242	XI	4	IV	XI
2	0.744	IX	4	IV	X
3	1.385	IV	5	I	II
4	1.457	III	5	I	I
5	1.545	II	4	IV	V
6	0.482	X	5	I	III
7	1.751	I	4	IV	IV
8	0.961	V	4	IV	VI
9	0.894	VI	4	IV	VII
10	0.769	VII	4	IV	VIII
11	0.769	VII	4	IV	VIII

Final Comprehensive Ranking: Daguan County, Zhaoyang District, Yongshan County, Yanjin County, and Yiliang County occupy the top positions in the comprehensive ranking. This indicates they not only hold critical positions in the network topological structure but also serve as pivotal hubs in actual traffic flow patterns within the regional transportation system.

4.2 Critical node identification

To evaluate network connectivity, nodes in Zhaotong City's expressway network were sequentially removed based on node importance rankings, deleting corresponding nodes and associated segments. The connectivity reliability index of the degraded network was then calculated. By optimizing influence factor A using Eq. (13) and Eq. (14), an optimal value of 0.75 was obtained. Substituting A and related metrics into Eq. (13) yielded the final topological potential ranking of nodes.For travel time reliability assessment, nodes were incrementally degraded according to importance rankings, with the traffic capacity of targeted nodes and connected segments reduced stepwise by 10% per stage until reaching 10% of initial capacity. Post-degradation travel time reliability was computed, and the cumulative impact of each node's degradation on network-wide reliability was aggregated to establish comprehensive reliability rankings. Nodes with lower numerical values demonstrate greater network-wide impact and higher criticality, as detailed in Table 2.

Table 2
Road network connectivity and comprehensive travel time reliability metrics

Connectivity reliability metrics after node removal			Topological potential ranking		Comprehensive travel time reliability ranking	
Removed node id	Relative size of largest connected component	Global network efficiency ratio	Node id	Topological potential	Node id	Comprehensive travel time reliability
4	0.83	0.94	5	7.72	4	43.92
5	0.91	0.83	7	6.82	5	46.01
3	0.73	0.70	3	6.54	3	47.16
9	0.91	0.97	9	4.82	7	47.48
10	0.91	1.05	2	4.42	9	56.72
11	0.91	1.03	8	4.38	11	57.94
1	0.91	1.09	4	4.13	8	58.18
7	0.73	0.73	11	3.56	10	59.89
8	0.91	0.98	10	2.86	6	69.67
2	0.82	0.88	6	1.67	2	70.13
6	0.91	1.07	1	1.29	1	71.16

By comprehensively considering both connectivity reliability and travel time reliability, the criticality of all nodes was calculated using Eq. (16), enabling the determination of critical nodes impacting road network reliability, as presented in Table 3. It can be observed from the table that Node 5 (Yiliang County) exhibits the highest criticality in Zhaotong City's expressway network. As illustrated in Fig.2, Yiliang County connects five major expressway segments (④, ⑦, ⑧, ⑨, and ⑩), which collectively handle substantial traffic volumes. Consequently, attacks targeting Node 5 would significantly degrade both connectivity reliability and travel time reliability across the entire network.

By contrast, Node 6 (Yongshan County) and Node 1 (Qiaojia County) occupy peripheral locations within the network topology (Fig.2). Disruptions to these nodes and their connected segments would exert comparatively minimal impact on overall network connectivity and travel time reliability metrics.

Table 3
Ranking of critical nodes impacted by road network reliability

Node id	Node criticality	Criticality rank
1	0.9135	I
2	0.9801	II
3	1.0606	III
4	1.0158	IV
5	1.0869	V
6	0.9237	VI
7	1.0659	VII
8	0.9982	VIII
9	1.0097	IX
10	0.9640	X
11	0.9816	XI

4.3 Critical segment identification

Based on the OD distribution volume data for Zhaotong City, Yunnan Province, projected for the planning year 2030, critical segments in the long-term network plan (2030) were identified. An ant colony algorithm program was developed in MATLAB to solve the stochastic user equilibrium model, with critical segments determined by traffic volume thresholds. During simulation, key parameters were configured as follows: local pheromone decay coefficient ρ = 0.001, global pheromone decay coefficient = 0.01, iteration count = 200, and path choice parameter θ in the logit model = 0.1. After solving the stochastic user equilibrium model via the ant colony algorithm, the program converged successfully, yielding traffic volume allocation results across all segments as visualized in Fig. 3.

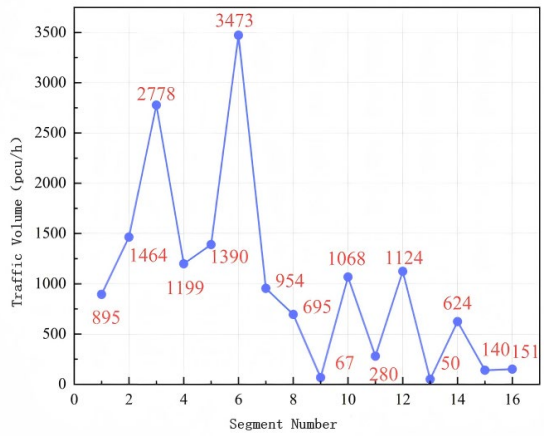

Fig. 3. Traffic volume distribution across segments in Zhaotong City road network model

Based on segment traffic volume data from counties/districts in Zhaotong City, a cumulative frequency histogram of segment flows was constructed. Using the 85th percentile cumulative probability value (1064 pcu/h) as the flow threshold, segments exceeding this value were identified as critical. Seven critical segments were determined according to traffic volumes:Daguan County – Yanjin County, Zhaoyang District – Daguan County, Ludian County – Zhaoyang District, Daguan County – Yongshan County, Zhaoyang District – Yiliang County, Yanjin County – Shuifu City, Yiliang County – Zhenxiong County, as detailed in Table 4.

Table 4
Critical segments in Zhaotong City

No.	Critical segment	Connected node cities
1	⑥	Daguan County – Yanjin County
2	③	Zhaoyang District – Daguan County
3	②	Ludian County – Zhaoyang District
4	⑤	Daguan County – Yongshan County
5	④	Zhaoyang District – Yiliang County
6	⑫	Yanjin County – Shuifu City
7	⑩	Yiliang County – Zhenxiong County

4.4 Identification of critical transport corridors under multi-objective framework

4.4.1 Feature line determination based on OD clustering analysis

An OD projection model was constructed to simulate the attraction potential of transport lines using OD demand distribution data across node cities. This enabled preliminary calculation of OD attraction volume and OD residual volume for each node connection. Subsequently, Eqs. (20) and (21) were applied to derive precise attraction and residual volumes. During analysis, key spatial parameters were configured with a segment subdivision precision of 2 km and an attraction radius of 50 km. Based on OD demand volumes of node cities, OD attraction and residual volumes for urban road segments were computed, as detailed in Table 5.

Table 5
OD feature lines OD attraction volume for node city segments

No.	Node city segment	OD attraction volume (pcu/h)	OD residual volume (pcu/h)	No.	Node city segment	OD attraction volume (pcu/h)	OD residual volume (pcu/h)
1	Qiaojia County – Ludian County	98.53	55.42	9	Yiliang County – Weixin County	92.79	52.19
2	Ludian County – Zhaoyang District	1206.53	678.67	10	Yiliang County – Zhenxiong County	1171.91	659.20
3	Zhaoyang District – Daguan County	3410.30	1918.29	11	Yanjin County – Suijiang County	1104.69	751.62
4	Zhaoyang District – Yiliang County	2371.21	1333.80	12	Yanjin County – Shuifu City	507.66	302.79
5	Daguan County – Yongshan County	640.59	360.33	13	Yanjin County – Weixin County	89.38	50.27
6	Daguan County – Yanjin County	5934.74	3338.29	14	Yanjin County – Zhenxiong County	872.87	554.95
7	Daguan County – Yiliang County	2121.88	1193.56	15	Suijiang County – Shuifu City	173.69	97.70
8	Yiliang County – Yanjin County	2232.52	1255.79	16	Weixin County – Zhenxiong County	75.37	42.39

To evaluate the correlation among urban road segments, influence coefficients between them were calculated, as shown in Table 6:

Table 6
Influence matrix for urban road feature lines

Influence coefficient	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1.00	0.95	0.98	0.98	0.91	0.99	0.97	0.98	0.40	0.95	0.95	0.89	0.38	0.94	0.68	0.26
2	0.85	1.00	0.80	0.71	0.06	0.89	0.68	0.70	0.86	0.42	0.39	0.25	0.87	0.22	0.74	0.89
3	0.95	0.37	1.00	0.19	0.67	0.68	0.10	0.14	0.95	0.39	0.42	0.74	0.95	0.54	0.91	0.96
4	0.93	0.10	0.61	1.00	0.52	0.78	0.37	0.40	0.93	0.12	0.17	0.62	0.93	0.35	0.87	0.94
5	0.73	0.70	0.89	0.85	1.00	0.94	0.83	0.84	0.74	0.69	0.67	0.29	0.75	0.59	0.52	0.79
6	0.97	0.64	0.02	0.29	0.81	1.00	0.36	0.33	0.97	0.65	0.67	0.85	0.97	0.74	0.95	0.98
7	0.92	0.01	0.65	0.50	0.46	0.80	1.00	0.47	0.92	0.02	0.07	0.57	0.93	0.27	0.85	0.94
8	0.92	0.04	0.63	0.47	0.49	0.79	0.41	1.00	0.93	0.07	0.12	0.60	0.93	0.30	0.86	0.94
9	0.47	0.96	0.98	0.98	0.92	0.99	0.98	0.98	1.00	0.96	0.95	0.90	0.42	0.94	0.70	0.31
10	0.85	0.45	0.81	0.72	0.03	0.89	0.69	0.70	0.86	1.00	0.40	0.23	0.86	0.24	0.74	0.89
11	0.87	0.38	0.78	0.68	0.15	0.87	0.65	0.66	0.88	0.36	1.00	0.32	0.88	0.14	0.77	0.90
12	0.67	0.75	0.91	0.87	0.53	0.95	0.86	0.86	0.69	0.74	0.73	1.00	0.70	0.65	0.43	0.75
13	0.49	0.96	0.99	0.98	0.92	0.99	0.98	0.98	0.46	0.96	0.95	0.90	1.00	0.94	0.71	0.33
14	0.82	0.54	0.84	0.77	0.13	0.91	0.74	0.75	0.83	0.53	0.50	0.09	0.84	1.00	0.69	0.86
15	0.01	0.92	0.97	0.96	0.85	0.98	0.95	0.96	0.05	0.92	0.91	0.81	0.09	0.89	1.00	0.23
16	0.57	0.96	0.99	0.98	0.93	0.99	0.98	0.98	0.54	0.96	0.96	0.92	0.53	0.95	0.76	1.00

4.4.2 Identification results of critical transport corridors under multi-objective framework

Segments in Zhaotong City were classified using fuzzy clustering methodology. First, the influence coefficient matrix was normalized via the max-normalization method. Subsequently, a fuzzy similarity matrix R was constructed using max-min composition, followed by deriving the transitive closure $t(R)$ through iterative squaring operations to obtain transitive relation $R \to R^2 \to R^4 \to R^8$. Given $R^8 \circ R^8 = R^8$, the fuzzy equivalence matrix $t(R) = R^8$ was established. Based on $t(R)$ -data, the λ-cut matrix size was iteratively adjusted to cluster similar segments, ultimately generating a dynamic clustering diagram as shown in Fig.4.

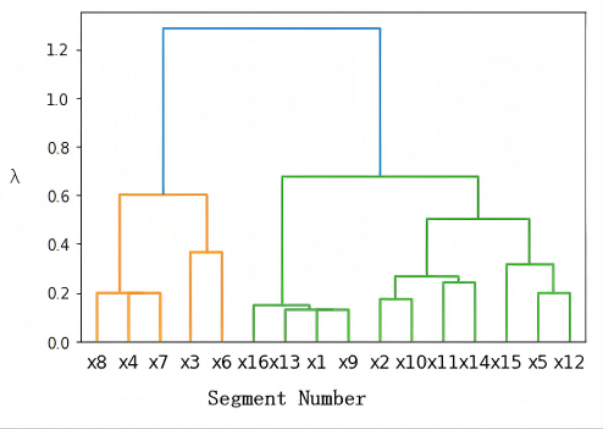

Fig. 4. Dynamic clustering diagram

Fig. 5. Critical transport corridors identification results in Zhaotong City

The optimal value of λ was calculated through the F-statistic and analyzed using MATLAB programming software. When $\lambda = 0.8$, the clustering results achieved the optimal state, ultimately yielding five categories of clustering results: [1, 5, 9, 12, 13, 15, 16], [2, 10, 11, 14], [3], [4, 7, 8], and [6]. According to the clustering results, different road segments are classified into the same category due to their similarities, meaning segments within each category exhibit similar characteristics. Combining the critical road segments identified earlier and their corresponding traffic volume data, Segment 5 and Segment 12 can be classified into one category, Segment 2 forms an independent category, Segments 3, 4, and 7 are classified into separate individual categories, and Segment 6 is also classified as an independent category. Since road segments across categories are of equivalent importance and exhibit similarities, to more precisely identify critical transport corridors, the segments with higher traffic volumes within each category were selected as core sections constituting the critical transport corridors. Therefore, the finally determined critical road segments are Segment 5, Segment 3, Segment 4, and Segment 6. Specific information is presented in Table 7.

Table 7
Critical segments identified based on fuzzy clustering

No.	Critical segment	Connected node cities	Traffic volume (pcu/h)
1	⑥	Daguan County – Yanjin County	3473
2	③	Zhaoyang District – Daguan County	2778
3	②	Ludian County – Zhaoyang District	1464
4	⑤	Daguan County – Yongshan County	1390
5	④	Zhaoyang District – Yiliang County	1199

These segments were combined into critical paths through geospatial connectivity, ultimately identifying three critical transport corridors: Ludian County–Zhaoyang District–Daguan County–Yanjin County, Ludian County–Zhaoyang District–Daguan County–Yongshan County, and Ludian County–Zhaoyang District–Yiliang County. The identified critical transport corridors are presented in Table 8. As the data used in this study are based on the 2030 planning data for Zhaotong City, Yunnan Province, these corridors represent the critical transport corridors for Zhaotong City in 2030.

Table 8
Critical transport corridors identification results

No.	Formed critical transport corridor	Connected node cities	Average traffic volume (pcu/h)
1	②-③-⑥	Ludian County–Zhaoyang District–Daguan County–Yanjin County	2572
2	②-③-⑤	Ludian County–Zhaoyang District–Daguan County–Yongshan County	1814
3	②-④	Ludian County–Zhaoyang District–Yiliang County	1427

The identified critical transport corridors in Zhaotong City were visualized as shown in Fig. 5. In the diagram, solid lines represent segments constituting critical transport corridors, with line thickness corresponding to traffic volume magnitude, while dashed lines denote segments of non-critical transport corridors.

5. Conclusion

(1) Innovation in node importance Measurement Model: A node importance model integrating static geometric features of complex networks with dynamic traffic flow characteristics was constructed. The improved entropy weight method quantified node indicator weights, and an *h*-index-based dynamic node importance measurement approach was proposed. By fusing static and dynamic features, Daguan County, Zhaoyang District, Yongshan County, Yanjin County, and Yiliang County were ranked highest in the case study.

(2) Proposal of Critical Node Identification Method: Based on road network reliability analysis, connectivity reliability and travel time reliability metrics applicable to expressway networks were defined. By investigating reliability trends under different node importance attack scenarios, Node 5 (Yiliang County) was successfully identified as the most critical node in Zhaotong City's expressway network.

(3) Critical Segment Identification Method: A quantitative critical segment identification method based on the stochastic user equilibrium model was proposed, combined with the ant colony algorithm to identify critical corridors. Seven critical segments were identified based on traffic volumes: Daguan County–Yanjin County, Zhaoyang District–Daguan County, Ludian County–Zhaoyang District, Daguan County–Yongshan County, Zhaoyang District–Yiliang County, Yanjin County–Shuifu City, and Yiliang County–Zhenxiong County.

(4) Multi-objective Critical Corridor Identification Method: The proposed multi-objective critical corridor identification method integrated node importance, critical nodes, and critical segments data analysis, providing a systematic framework for corridor identification. Three critical transport corridors were ultimately identified: Ludian County–Zhaoyang District–Daguan County–Yanjin County, Ludian County–Zhaoyang District–Daguan County–Yongshan County, and Ludian County–Zhaoyang District–Yiliang County.

(5) Research Limitations and Future Work: The intrinsic relationships among node importance indicators require deeper exploration, necessitating precise differentiation of weight coefficients and contribution rates. Critical node identification considered only single-node attacks; future studies should investigate simultaneous multi-node attacks to enhance practical applicability. Additionally, as the case study used simplified network structures, model validation through large-scale road network data is essential.

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