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Path-Dependent Infrastructure Planning: A Network Science-Driven Decision Support System with Iterative TOPSIS

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Abstract

Expressway networks represent evolving complex systems whose topological properties significantly impact regional development. This paper presents a decision support framework for addressing the expressway infrastructure sequencing problem using computational intelligence. We develop a novel framework that models expressways as L-space networks and evaluates how construction sequences create path-dependent evolutionary trajectories, introducing network science principles into infrastructure planning decisions. Our decision support framework quantifies project impacts on accessibility, connectivity, and reliability using nine topological metrics and a hybrid weighting mechanism that combines domain expertise with entropy-based uncertainty quantification. The system employs a hybrid TOPSIS algorithm that relies on geometric symmetry to simulate network evolution, capturing emergent properties in which each decision restructures possibilities for subsequent choices—a computational challenge that conventional planning approaches have not addressed. The system was validated with real-world Chongqing expressway planning data, demonstrating its ability to identify sequences that maximize synergistic network effects. Results reveal how topologically equivalent projects produce dramatically different system-wide outcomes depending on implementation order. Analysis shows that network science-informed sequencing substantially enhances system performance by exploiting structural synergies. This research advances decision support frameworks by bridging complex network theory with computational decision-making, creating a novel analytical tool that enables transportation authorities to implement evidence-based infrastructure sequencing strategies beyond the reach of conventional planning methods.

Keywords: decision support system; infrastructure sequencing optimization; complex network analysis; hybrid TOPSIS; path-dependent evolution

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1. Introduction

Transportation infrastructure, particularly expressway networks, represents a paradigmatic example of a complex adaptive system whose evolutionary dynamics profoundly influence socioeconomic development patterns across multiple scales. As these networks evolve, they exhibit emergent topological properties that go beyond simple aggregation of individual expressway segments, creating nonlinear relationships between infrastructure investment and system-wide performance. The progressive development of expressway systems has transformed them into critical national infrastructure, integrating economic, social, and strategic functions through their complex networks of connections. Recent global disruptions have highlighted the pivotal role of these networks, as the post-pandemic recovery has triggered unprecedented demands on expressway systems—manifesting through intensified e-commerce logistics, resurgent inter-regional tourism, and strengthened industrial collaboration networks [1]. These emergent usage patterns serve as both indicators and catalysts of economic recovery, creating feedback loops that drive further network evolution. China's National Expressway Network Plan exemplifies this evolutionary process, projecting network expansion to approximately 162,000 km by 2035, including 53,000 km of new expressway projects strategically designed to enhance corridor capacity between urban agglomerations, while simultaneously improving network efficiency and resilience through topological optimization [2]. This expansion represents a fascinating case study in network growth, where scale-free properties emerge from localized development decisions.

Resource constraints create boundary conditions that transform construction sequencing into a complex optimization problem characterized by path dependency and irreversibility. The temporal dimension introduces critical nonlinearities, as each construction decision reconfigures the topological solution space for subsequent decisions, creating unique evolutionary pathways with divergent long-term outcomes [3]. Similar path-dependent and iterative evolution mechanisms have also been examined in complex network and multi-agent system research, where global system behaviors emerge from repeated local interactions under asynchronous decision-making and communication delays, highlighting how sequential interactions shape long-term convergence trajectories in networked systems [4,5]. In mountainous regions with heterogeneous geographical constraints, these path dependencies become more pronounced, as topographical features introduce additional nonlinearities that amplify the consequences of sequencing decisions [6]. Research on infrastructure construction sequencing aims to scientifically determine the sequence and timing of projects to optimize resource allocation and enhance overall benefits (such as economic, social, and network effects). The core of this approach involves quantifying project priority using multidimensional indicators while incorporating dynamic constraints (such as funding, land availability, and policy considerations) to maximize overall benefits [7,8]. This presents a significant challenge for decision support frameworks, requiring advanced computational techniques to process complex network dynamics and provide actionable recommendations to transportation authorities.

Infrastructure sequencing optimization represents a complex multi-objective problem characterized by nonlinear dynamics and emergent properties. Current methodologies addressing this challenge can be categorized into four distinct approaches, each capturing different aspects of the sequencing problem while exhibiting specific limitations in addressing the full complexity of network evolution [9]. Multi-attribute decision frameworks transform sequencing challenges into multi-criteria evaluation problems, employing techniques such as TOPSIS [10], which ranks alternatives based on Euclidean distances to ideal solutions, and VIKOR [11], which incorporates both group utility and individual regret values to mitigate TOPSIS's ranking reversal issues. These methodologies typically

treat infrastructure projects as discrete entities with static properties, overlooking the dynamic interdependencies that emerge as networks evolve and change over time. While computationally tractable, these approaches fail to capture the bifurcation points and phase transitions that characterize the development of complex networks, where small perturbations in the construction sequence can lead to dramatically different system-wide behaviors through self-reinforcing feedback mechanisms.

Network effect dynamic optimization approaches recognize that infrastructure exhibits non-additive properties, where newly constructed elements fundamentally alter the topological structure and functional characteristics of the existing network [7]. These methodologies apply complex network theory to quantify emergent properties, such as network efficiency and accessibility, and simulate network growth trajectories to optimize construction timing [11]. However, most implementations still employ linear superposition principles when evaluating network modifications, failing to fully capture the path-dependent nature of network evolution, where early decisions constrain the solution space for subsequent choices through topological lock-in effects. Combined subjective-objective weighting methods attempt to balance expert judgment with data-driven approaches, integrating the Analytic Hierarchy Process with entropy-based methods to determine indicator weights [12]. This hybrid approach addresses the uncertainties inherent in evaluating complex systems. However, it typically applies static weighting schemes that remain constant throughout network evolution, overlooking how the relative importance of different performance metrics may shift as networks cross critical thresholds. Dynamic sequence iterative optimization transforms static sequencing into multi-stage problems, updating network status and priorities after each infrastructure addition [13,14]. While this approach acknowledges the path-dependent nature of network evolution, most implementations employ simplistic update mechanisms that fail to capture the nonlinear cascading effects characteristic of complex networks, in which topological modifications can propagate through the system in ways that transcend local connectivity changes.

The evaluation metrics underpinning these methodologies have evolved from unidimensional to multidimensional frameworks that examine different aspects of infrastructure performance. Connectivity metrics [15,16] assess structural integrity, while network efficiency indicators [17] measure transportation performance via shortest-path analysis. Accessibility measures [18] evaluate spatial coverage, and location coefficients [19] identify critical nodes using centrality metrics. Network scale rationality [20] examines the correspondence between infrastructure development and socioeconomic factors. While comprehensive, these metrics are typically applied in isolation or through simple weighted aggregation, failing to capture the complex interdependencies and synergies among different performance dimensions. Despite these advances, current approaches exhibit three fundamental limitations when addressing complex infrastructure sequencing challenges. First, they employ fragmented evaluation perspectives that fail to capture the holistic properties of networks as complex adaptive systems, in which global behaviors emerge from local interactions that cannot be predicted by reductionist analysis. Second, they inadequately account for the dynamic evolution of networks, where each modification triggers cascading effects that reconfigure the entire system's response landscape through self-organizing processes. Third, they neglect the synergistic effects among different network elements, in which the contribution of individual components depends on their positions within the evolving network topology.

These limitations are particularly evident in computational approaches such as genetic algorithms [21], neural networks, and particle swarm optimization [22], which require extensive high-quality data and often converge to local optima rather than global solutions [23]. Similarly, bi-level planning models [24,25] are poorly applicable to discrete network configurations and face computational challenges when applied to large-scale

systems. Furthermore, while complex network metrics, such as degree distribution, centrality measures, and network density, are widely applied to quantify connectivity and accessibility [26,27], and their evolution typically follows preferential attachment principles, transitioning from linear to grid-like configurations, these intrinsic network properties are rarely integrated into construction sequencing methodologies. The evolutionary dynamics of expressway networks exhibit scale-free properties, offering good robustness against random disruptions but vulnerability to targeted attacks [18]. This highlights the importance of protecting critical nodes, promoting balanced regional development, and implementing adaptive management strategies [17]. However, these fundamental characteristics of complex networks remain largely unincorporated in conventional sequencing approaches. This disconnect between network science theory and infrastructure planning practice underscores the need for an integrated framework that accounts for expressway construction sequencing from a systems perspective, embracing complexity, emergence, and nonlinear dynamics.

This research addresses fundamental limitations in infrastructure sequencing by developing a decision support framework that reconceptualizes expressway construction through the lens of complex network theory and computational intelligence. Our novel contributions include the following: I. An integrated decision support framework that synthesizes network science principles with multi-criteria decision-making to capture the synergistic effects of sequencing decisions on network-wide performance through iterative simulation of evolutionary trajectories. II. A hybrid computational methodology combining L-space network representation with an enhanced TOPSIS algorithm that employs a dual expert-entropy weighting mechanism to address uncertainty quantification in complex network evaluation. III. A path-dependent modeling approach that mathematically formalizes how each construction decision restructures the possibility space for subsequent choices—a computational challenge unaddressed by conventional planning methods.

We extend traditional planning approaches by establishing a comprehensive evaluation system centered on accessibility, connectivity, and reliability metrics for a dynamic network that captures emergent properties during evolution. Our L-space network representation enables mathematical formalization of how infrastructure projects propagate topological modifications throughout the network. The hybrid expert-entropy weight TOPSIS methodology combines subjective expertise with objective data characteristics, providing a robust computational foundation for decision-making. Applied to Chongqing's Expressway Planning, our decision support framework demonstrates how construction decisions create path-dependent evolutionary trajectories with divergent outcomes. This research bridges complex systems theory and practical infrastructure planning through computational intelligence, recognizing expressway networks as complex adaptive systems in which global behaviors emerge from local interactions—essential for infrastructure planning amid increasing complexity and resource constraints.

The remainder of this paper is structured as follows: Section 2 presents the research object and data processing. Section 3 details the methodological framework of our decision support framework, including the network representation model, topological indicators, and hybrid TOPSIS algorithm. Section 4 presents the application to a case study of Chongqing's expressway planning, including the experimental design and computational results, along with an analysis of evolutionary trajectories. Section 5 discusses the theoretical and practical implications, limitations, and future research directions of computational intelligence for infrastructure planning.

2. Research Object and Data Processing

2.1. Study Area and Knowledge Base Development

Chongqing's expressway network serves as an ideal testbed for our decision support framework, having evolved over three decades into a sophisticated three-ring, fourteen-radial, multi-connecting configuration. This network's path-dependent development patterns, coupled with Chongqing's challenging mountainous topography, create a computationally complex sequencing problem that demands advanced intelligence techniques. As of 2022, the system has achieved network density preeminence among Western China's infrastructure systems, providing rich historical evolution data for our knowledge-based system.

To construct the knowledge base for our decision support framework, we systematically acquired, validated, and integrated three complementary data categories (illustrated in Figure 1): (i) expressway network GIS data obtained from the CSDN platform, (ii) toll station geospatial and operational data, and (iii) district/county administrative center locations extracted via Gaode Map API. These heterogeneous datasets were processed using the Geopandas computational library to generate a comprehensive Shapefile representation suitable for network science analysis.

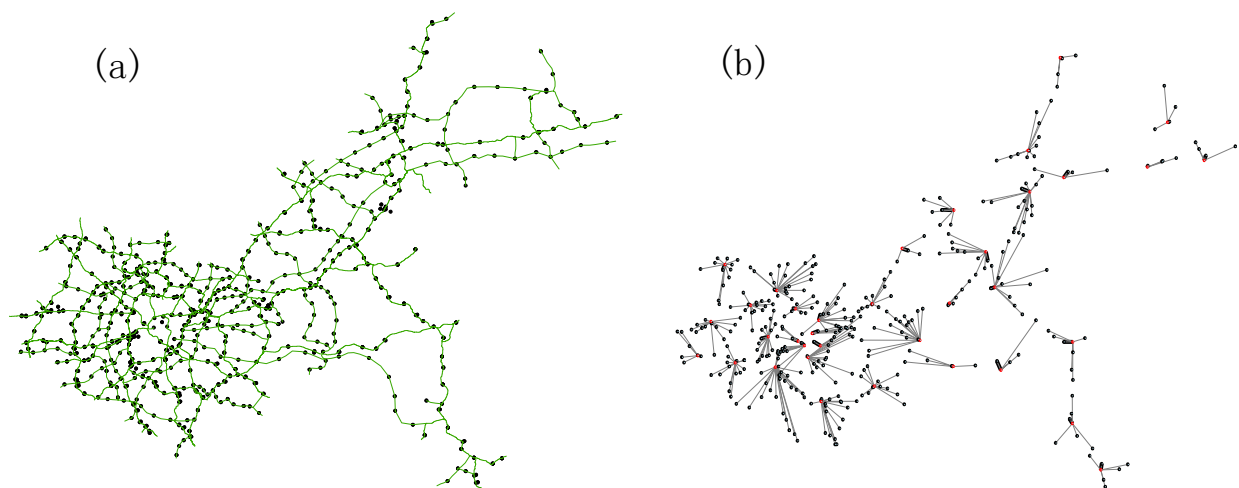


Figure 1. (a) The distribution of expressways (marked as green lines) and toll stations (marked as black points) in Chongqing. (b) The connection network between district-level administrative centers (marked as red points) and toll stations (marked as black points).

The knowledge acquisition process extracted 19 critical parameters from Chongqing's expressway GIS layer, organized into three semantic categories: (1) route fundamentals (route number, name, administrative division, and operation year); (2) spatial characteristics (origin-destination coordinates, actual mileage, and length); and (3) technical specifications (lane configuration and design speed). These attributes constitute the network's foundational information matrix, which supports computational inference processes. The expressway toll station GIS layer contributed 10 additional parameters, primarily comprising station identifiers (code and name), precise locational data (geographic coordinates and pile reference), and administrative information (reporting hierarchy and implementation timeline). District and county administrative center coordinates, retrieved through Gaode Map API, provided three essential parameters: object identification, administrative designation, and precise geographic positioning.

2.2. Knowledge Engineering and Network Construction

The multi-source, heterogeneous nature of our dataset necessitated sophisticated knowledge engineering before constructing the computational model. We implemented a systematic approach using ArcGIS 10.8 and NetworkX 3.2.1 to verify coordinates, perform topological rectification, and analyze spatial correlations, establishing a foundation for an accurate representation of the expressway network. Our methodology comprised three principal computational stages:

First, we executed a rigorous verification algorithm for the geographical coordinates of both toll stations and administrative centers. Using the Gaode Map API V4.2.0 for reverse geocoding, we obtained precise longitude and latitude coordinates for Chongqing's district/county administrative centers and toll facilities. Each entry underwent automated validation by cross-referencing returned geographical designations against authoritative administrative classifications and by employing rule-based consistency checking to ensure the spatial integrity of nodal elements.

Second, we developed a comprehensive topological correction procedure for the GIS data of the expressway network. After importing route geographical information from shapefile formats into ArcGIS, we standardized data source encoding to UTF-8 to ensure compatibility with Python 3.9 processing environments. Our system used GeoPandas 1.0.1 for systematic data quality assessment and visualized stations and routes using NetworkX. For identified topological inconsistencies, including disjointed route segments, we applied ArcGIS computational topology rules to merge unconnected endpoints (hub points and route nodes), thereby establishing a coherent expressway connection framework essential for subsequent geometric and topological analyses.

Finally, we constructed a representation based on the L-space network representation from complex network theory, generating a weighted expressway network $G = (V, E)$, where V denotes the set of nodes, and E denotes the set of edges. In network modeling, different representations capture different types of relationships. In the L-space representation, nodes represent physical infrastructure elements in expressway systems, and edges represent direct physical connections between adjacent facilities. In contrast, P-space represents connections based on shared routes or services, C-space focuses on co-occurrence relationships along routes, and B-space describes bipartite relationships between routes and stations. This study focuses on the structural performance of expressway networks. The analysis is based on the staged addition of new expressway lines and aims to support construction sequencing decisions. For this purpose, the L-space representation is more suitable than alternative representations. Moreover, it is worth noting that the term “network” refers to an abstraction of the expressway system used to describe its overall topological structure, whereas a “graph” represents the mathematical formulation of the network topology. To avoid conceptual confusion, the terms network and graph are not strictly distinguished in the remainder of this paper when no ambiguity arises and are collectively referred to as a network. Within this computational model, node set V encompasses dual elements: toll station nodes and county administrative center nodes. Similarly, edge set E comprises two distinct connection types: (1) linkages between district/county administrative centers and their jurisdictional toll stations, weighted by shortest navigation distance; and (2) connections between adjacent toll stations within the expressway network, weighted by actual path length. This weighted network construction enables our decision support system to capture both administrative hierarchies and physical infrastructure characteristics, providing the computational foundation for the topological analysis algorithms in our decision support framework.

The resulting knowledge base serves as the foundation for our decision support framework, enabling both the representation of the current expressway network state and

the simulation of potential future evolutionary trajectories. This computational model encapsulates the essential topological, spatial, and operational characteristics of Chongqing's expressway system, enabling our decision support framework to analyze the complex path-dependent dynamics of infrastructure sequencing decisions.

3. Methodology

3.1. The Expert Scoring Method (EC)

In the domain of highway transportation construction planning, the expert scoring method has been widely employed as a critical basis for decision-making in determining the construction sequencing of highway projects, thereby evaluating and prioritizing candidate expressway projects [28], especially during the early stages of transportation planning and throughout project prioritization processes. It is particularly suitable for contexts where quantitative data remain relatively scarce, and qualitative factors predominate in decision-making.

The evaluation criteria of the expert scoring method are primarily constructed around the key influential factors in expressway construction sequencing decisions, including demand urgency, comprehensive benefits, engineering feasibility, and policy alignment (as presented in Table 1). The indicator configuration emphasizes the assessment of current transportation bottleneck severity, passenger and freight transport demand magnitude, comprehensive economic and social benefits, construction difficulty levels, assurance of resource elements, and the degree of conformity between projects and national and provincial transportation development plans.

Table 1. Expert Scoring Evaluation Indicator System for Expressway Construction Sequencing.

Primary Indicators	Secondary Indicators	Indicator Definition
Demand Urgency (λ_1)	Current Transportation Bottleneck Severity (θ_1)	Average daily congestion duration of the current corridor
	Passenger and Freight Demand Scale (θ_2)	Projected annual average daily passenger flow and freight flow
Comprehensive Benefits (λ_2)	Economic Benefits (θ_3)	Number of industrial parks and logistics hubs covered
	Social Livelihood Benefits (θ_4)	Number of counties covered and poverty-alleviated counties
Engineering Feasibility (λ_3)	Construction Difficulty (θ_5)	Geological conditions and demolition volume
	Resource Assurance (θ_6)	Capital availability rate and land supply feasibility
Policy Alignment (λ_4)	Planning Compatibility (θ_7)	Whether designated as a national or provincial strategic corridor

Note: λ_k and θ_j denote weight coefficients satisfying $\sum_{k=1}^4 \lambda_k = 1$ and $\sum_{j=1}^7 \theta_j = 1$, with primary and secondary weights subject to hierarchical consistency constraints: $\lambda_1 = \theta_1 + \theta_2$, $\lambda_2 = \theta_3 + \theta_4$, $\lambda_3 = \theta_5 + \theta_6$, and $\lambda_4 = \theta_7$.

To ensure the comparability and consistency of scoring results, quantitative or semi-quantitative scoring criteria are explicitly established for each evaluation indicator. Indicator weights are determined through expert consultation, whereby multiple experts with relevant practical experience reach consensus through thorough deliberation. The expert panel comprises professionals from transportation planning, highway engineering, regional economics, and policy research. All experts independently evaluate each candidate expressway project within a unified framework of indicator definitions and scoring criteria, employing a 1–5 point scale.

To mitigate the influence of individual subjective judgment bias on evaluation outcomes, during data processing, the highest and lowest expert scores for each indicator of each route are excluded before calculating the arithmetic mean, which serves as the final score for that indicator. Upon completion of all expert scoring, a weighted summation of secondary indicator scores yields the comprehensive evaluation score for each expressway project, as shown in Equation 1. The sequence is determined in descending order. Let there be a total of m candidate expressway projects. For any project i ($i = 1, 2, \dots, m$), its comprehensive evaluation score is defined as follows:

$$S_i = \sum_{j=1}^7 \theta_j \bar{x}_{ij}. \quad (1)$$

where S_i denotes the comprehensive evaluation score of project i , with higher values of S_i indicating greater construction priority; θ_j represents the weight coefficient of the j -th secondary indicator; and $\bar{x}_{ij}$ denotes the final score of project i on the j -th secondary indicator, derived from original expert scores through the procedure of excluding the highest and lowest values before averaging. If there are p experts in total, and the original score assigned by the r -th expert is denoted as $x_{ij}^{(r)}$, then

$$\bar{x}_{ij} = \frac{1}{p-2} \left(\sum_{r=1}^p x_{ij}^{(r)} - \max_r x_{ij}^{(r)} - \min_r x_{ij}^{(r)} \right) \quad (2)$$

3.2. Proposed Method

3.2.1. Knowledge-Based Evaluation Framework for Expressway Networks

Our decision support framework incorporates a novel knowledge-based evaluation framework that synthesizes domain-specific planning metrics with computational network science to capture emergent properties of complex expressway systems. This cognitive architecture integrates three functional dimensions—accessibility, connectivity, and reliability—operationalized through nine quantifiable indicators that collectively characterize network topology at both local and global scales (Table 2), creating a comprehensive knowledge representation for infrastructure assessment. The selected indicators integrate both traditional expressway planning metrics and classical complex network measures. Planning-oriented indicators are commonly used in transportation engineering to describe network coverage, connectivity, and accessibility from an infrastructure supply perspective, while complex network metrics are widely adopted to capture structural characteristics such as path efficiency, robustness, and vulnerability. The final set of nine indicators was determined through expert consultation with transportation planning and expressway engineering professionals, ensuring that the selected metrics are both theoretically grounded and practically meaningful for construction sequencing and network performance evaluation.

Table 2. Multidimensional knowledge representation framework for expressway network evaluation.

Dimension	Indicator	Knowledge Representation	Optimization Direction
Accessibility	Network Coverage Ratio	Proportion of geographic area and economic indicators covered by the expressway network	↑
	Network Density	Total length of expressways per unit area	↑
	Detour Ratio	The deviation between the actual travel distance and the spatial distance	↓
Connectivity	Connectedness	Connection strength within the expressway network	↑
	Average Path Length	Average shortest path distance between all pairs of nodes	↓

Reliability	Clustering Coefficient	Average proportion of connections among a node's neighbors	↑
	Small-World Coefficient	The extent to which a network exhibits small-world properties with high clustering and short path characteristics	↑
	Betweenness Centrality	Proportion of all shortest paths in the network that pass through a specific edge/node	↑
	Robustness	The network's ability to maintain functionality under failures or attacks	↑

Accessibility

The accessibility dimension of our decision support framework quantifies the spatial coverage and efficiency of expressway networks through computational metrics derived from normative planning standards established by the Ministry of Transport [28]. These accessibility indicators enable the assessment of the infrastructure's spatial service capacity.

(1) Network Coverage Ratio (ω_g)

ω_g measures the proportion of geographic area, population, or economic activity served by the expressway network [28]:

$$\omega_g = \frac{D_g}{D}, \quad (3)$$

where D_g denotes the covered indicators (e.g., administrative nodes, land area), and D denotes their total value within the study area. Higher values (approaching 1) indicate a more balanced spatial distribution, enhancing regional economic integration. This metric provides the decision support system with critical knowledge about service gaps in the transportation network.

(2) Network Density (γ_g)

Network density quantifies infrastructure concentration per unit area [28]:

$$\gamma_g = \frac{L_g}{A}, \quad (4)$$

where γ_g represents the expressway network density, defined as the expressway length per unit area (km/100 km²), L_g denotes the total expressway mileage (km), and A indicates the area of the region (100 km²). This metric directly correlates with traffic-carrying capacity and provides the decision support framework with knowledge of infrastructure concentration.

(3) Detour Ratio (Y_g)

The detour ratio (Y_g) employs computational geometry to evaluate network efficiency by comparing actual versus Euclidean distances [28]:

$$Y_g = \frac{2}{N(N-1)} \sum_{i \neq j} y(i, j), \quad (5)$$

$$y(i, j) = \frac{d(i, j)}{d_s(i, j)}, \quad (6)$$

where N is the total number of nodes in the network, $y(i, j)$ represents the detour ratio between nodes v_i and v_j , $d(i, j)$ is their shortest path distance, and $d_s(i, j)$ is their Euclidean distance (km). Values approaching 1 indicate optimal spatial efficiency. This knowledge representation enables the decision support framework to assess network-geometry optimization.

Connectivity

Connectivity indicators capture the topological structure of expressway networks through complex network metrics that measure both local and global connection patterns.

(1) Connectedness (C_g)

C_g quantifies the overall connection strength normalized by topographical constraints [28]:

$$C_g = \frac{L_g}{\frac{\delta}{\sqrt{N \cdot A}}}, \quad (7)$$

where δ represents a terrain correction coefficient (1.2 for Chongqing's mountainous topology). Networks with $C_g \cong 1$ indicate fundamental completeness, while $C_g \in (2, \infty)$ signifies highly developed systems. This metric enables the decision support framework to account for geographical constraints in its reasoning process.

(2) Average Path Length ($\langle g \rangle$)

The average path length measures global connectivity efficiency through mean topological distance [29]:

$$\langle g \rangle = \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N \bar{g}(i, j), \quad (8)$$

$$\bar{g}(i, j) = \frac{\sum_{x \in [1, c_{ij}]} g_x(i, j)}{c_{ij}}, \quad (9)$$

where $\bar{g}(i, j)$ denotes the average distance between nodes v_i and v_j , $g_x(i, j)$ represents the x -th path distance, and c_{ij} denotes the total number of paths connecting v_i and v_j . This computational metric provides the decision support framework with knowledge of global network efficiency.

(3) Clustering Coefficient ($\langle C \rangle$)

The clustering coefficient [30] quantifies local connectivity through neighborhood interconnection density:

$$\langle C \rangle = \frac{1}{N} \sum_{i=1}^N C(i), \quad (10)$$

$$C(i) = \frac{2L(i)}{k(i)[k(i) - 1]}, \quad (11)$$

where $C(i)$ describes the closeness of connections between nodes v_i with degree $k(i)$ and its neighboring nodes, and $L(i)$ represents actual connections among neighbors of node v_i with degree $k(i)$. Higher coefficients indicate stronger regional connectivity clusters that enhance route diversity. This metric enables the decision support framework to identify local connectivity patterns.

(4) Small-World Coefficient (σ_g)

Whether a network exhibits small-world characteristics [31] can be determined by calculating its small-world coefficient. σ_g evaluates network efficiency through comparison with random equivalent structures:

$$\sigma_g = \frac{\langle c \rangle \langle g \rangle}{c_r g_r}, \quad (12)$$

where c_r and g_r represent the clustering coefficient and average path length of an equivalent random graph. Values exceeding 1 indicate small-world properties that optimize the trade-off between local clustering and global efficiency. This advanced network

science metric enables our decision support framework to identify efficient topological configurations.

Reliability

Reliability indicators are a key innovation in our framework, which evaluates network robustness against disruptions by capturing system resilience through topological analysis [32].

(1) Edge Betweenness (B_g)

Betweenness centrality identifies critical infrastructure components through centrality analysis:

$$B_g = \sum_{i=1}^M [\max_{e \in E} B_e - B(i)], \quad (13)$$

$$B(i) = \sum_{j \neq i \neq k} \frac{b_{j,k}(i)}{b_{j,k}}, \quad (14)$$

where $\max_{e \in E} B_e$ denotes the maximum value of edge betweenness centrality among all edges, $B(i)$ represents the betweenness centrality of edge e_i , and M is the total number of edges in the network; $b_{j,k}$ represents the number of shortest paths between edges e_j and e_k , and $b_{j,k}(i)$ denotes the number of shortest paths between edge e_j and edge e_k that pass through edge e_i . B_g measures betweenness variance, quantifying network dependence on critical “bridge” segments [33]. This metric enables the decision support system to identify vulnerability points.

(2) Network Robustness (R_g)

Network robustness quantifies system resilience against targeted disruptions:

$$R_g = \int_0^N S_e, \quad (15)$$

where S_e represents relative network efficiency. The calculation formula for S_e is as follows:

$$S_e = \frac{E'_f}{E_f}, \quad (16)$$

$$E'_f = \frac{2}{N'(N' - 1)} \sum_{i \neq j} \frac{1}{d'(i, j)}, \quad (17)$$

where E_f denotes the initial global efficiency of the network before any disruptions, E'_f represents the residual network efficiency after disruptions, N' is the largest connected component size, and $d'(i, j)$ represents the shortest path length. Our decision support framework assesses network robustness using intelligent attack-simulation algorithms that selectively target the most critical expressway segments, mimicking the impacts of catastrophic events [34].

This integrated evaluation framework transcends traditional planning approaches by capturing the emergent properties of expressway networks as complex adaptive systems. By synthesizing accessibility metrics from conventional planning with connectivity and reliability indicators from network science, our methodology enables a comprehensive assessment of how construction sequencing decisions propagate through network topology, revealing synergistic effects that reductionist evaluation approaches cannot capture.

3.2.2. Hybrid Computational Intelligence for TOPSIS Methodology

To quantify the complex, nonlinear impacts of construction decisions on network evolution, we developed a novel hybrid expert-entropy-weighted TOPSIS methodology

(HT) that integrates objective data characteristics with domain expertise through advanced computational intelligence. TOPSIS's geometric formulation is inherently symmetry-based, evaluating relative performance through symmetric distances to ideal and anti-ideal solutions [35]. This approach addresses the fundamental limitations of conventional multi-criteria decision frameworks that rely on either purely subjective weights (overlooking data patterns) or purely objective weights (neglecting contextual domain knowledge). Compared with other multi-criteria decision-making methods, TOPSIS does not require complex pairwise comparisons or strict consistency tests, and it can handle a large number of alternatives at a low computational cost. This makes it suitable for iterative evaluation, where project priorities need to be updated after each construction decision. In addition, TOPSIS allows multiple indicators to be included simultaneously, and it can directly reflect changes in indicator values driven by network evolution. The mathematical formulation of our hybrid methodology proceeds through six systematic stages:

(1) Construction of Normalized Evaluation Matrix

For each candidate project, we calculate its impact on all nine network performance indicators when integrated into the existing expressway system, forming the initial evaluation matrix X :

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} (1 \leq i \leq m, 1 \leq j \leq n), \quad (18)$$

where m denotes the number of candidate projects, n represents the number of evaluation indicators, and x_{ij} is the initial evaluation value of the j -th indicator when the i -th project is added to the network. To eliminate dimensional differences among indicators with different units and scales, the decision matrix is normalized using the min–max normalization method. For positive indicators, the normalized value is calculated as follows:

$$y_{ij} = \frac{x_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)}, \quad (19)$$

while for negative indicators, the normalized value is calculated as follows:

$$y_{ij} = \frac{\max(X_j) - x_{ij}}{\max(X_j) - \min(X_j)}, \quad (20)$$

where $\max(X_j)$ and $\min(X_j)$ denote the maximum and minimum values of the j -th indicator across all candidate projects, respectively.

This preprocessing produces the standardized evaluation matrix Y :

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} (1 \leq i \leq m, 1 \leq j \leq n). \quad (21)$$

(2) Hybrid Weight Determination Through Computational Intelligence

The information entropy of the j -th indicator is calculated to quantify its discriminatory power:

$$E_j = -\ln(m)^{-1} \sum_{i=1}^m p_{ij} \ln(p_{ij}), \quad (22)$$

where p_{ij} represents the proportion of the j -th indicator value for the i -th project.

$$p_{ij} = \frac{y_{ij}}{\sum_{j=1}^n y_{ij}}. \quad (23)$$

If $p_{ij} = 0$, then $p_{ij} \ln(p_{ij})$ is defined as 0 by limit continuity. The entropy-based weight w_j^E for each indicator is then derived as follows:

$$w_j^E = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)}. \quad (24)$$

In parallel, our decision support framework obtains expert-assigned weights w_j^A via the Analytic Hierarchy Process (AHP), which captures domain knowledge of the relative importance of different network properties. The hybrid weight W_j synthesizes both components through fusion:

$$W_j = \alpha w_j^E + (1 - \alpha) w_j^A, \quad (25)$$

where w_j^E and w_j^A denote the entropy-based weight and the AHP-based expert weight of the j -th indicator, respectively, and α is the integration coefficient (set to 0.7 based on expert consensus), which balances data-driven objectivity with expert judgment by giving greater weight to the entropy-based weights. The value of α is adjustable and can be modified in future applications according to specific research needs. This hybrid weighting mechanism captures both the intrinsic information contained in network topology data and the contextual knowledge of infrastructure planning experts, addressing a key limitation of conventional TOPSIS implementations that rely on static, non-adaptive weighting schemes.

(3) Construction of Weighted Normalized Matrix Through Computational Reasoning

The weighted normalized matrix V incorporates indicator importance into the evaluation:

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} y_{11} \cdot W_1 & y_{12} \cdot W_2 & \cdots & y_{1n} \cdot W_n \\ y_{21} \cdot W_1 & y_{22} \cdot W_2 & \cdots & y_{2n} \cdot W_n \\ \vdots & \vdots & \vdots & \vdots \\ y_{m1} \cdot W_1 & y_{m1} \cdot W_2 & \cdots & y_{mn} \cdot W_n \end{bmatrix} \quad (26)$$

(4) Determination of Ideal Solutions Through Computational Optimization

The positive ideal solution V^+ represents the hypothetical optimal network configuration identified through computational reasoning:

$$V^+ = \left\{ \max_{1 \leq i \leq m} v_{ij} \mid j = 1, 2, \dots, n \right\} = \{V_1^+, V_2^+, \dots, V_n^+\} \quad (27)$$

The negative ideal solution V^- represents the worst possible configuration:

$$V^- = \left\{ \min_{1 \leq i \leq m} v_{ij} \mid j = 1, 2, \dots, n \right\} = \{V_1^-, V_2^-, \dots, V_n^-\} \quad (28)$$

(5) Calculation of Euclidean Distances Through Computational Geometry

The distance between each project's impact and the ideal solutions quantifies its relative merit:

$$D_i^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^+)^2} \quad (1 \leq i \leq m) \quad (29)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^-)^2} \quad (1 \leq i \leq m) \quad (30)$$

(6) Calculation of the Relative Closeness Coefficient Through Decision

T_i provides a comprehensive metric for prioritizing projects:

$$T_i = \frac{D_i^-}{D_i^+ + D_i^-} (0 \leq T_i \leq 1). \quad (31)$$

This coefficient represents the synergistic contribution of each project to network performance, with higher values indicating a greater priority. The project with the maximum T_i is selected for immediate implementation, and the network topology is updated accordingly before initiating the next evaluation iteration.

Our hybrid TOPSIS methodology transcends conventional multi-criteria evaluation frameworks in three critical dimensions: I. Dynamic Path-Dependency Analysis: The system dynamically reassesses project priorities after each network modification, implementing a form of computational path-dependent reasoning that captures emergent evolutionary effects.

II. Adaptive Knowledge Fusion: The decision support framework intelligently integrates both objective data patterns and expert knowledge through an adaptive weighting mechanism with human expertise. III. Topological Impact Modeling: Rather than treating projects as isolated components, our system evaluates them based on their holistic impact on network topology through complex systems simulation. This approach conceptualizes expressway sequencing as an emergent property of complex network evolution rather than a static optimization problem. By implementing step-wise reconfiguration simulation of network topology, our decision support framework reveals how early construction decisions create path dependencies that constrain future possibilities—a fundamental characteristic of complex adaptive systems that remains unaddressed in conventional infrastructure planning frameworks. This computational capability enables transportation authorities to implement evidence-based infrastructure sequencing strategies that leverage topological synergies, surpassing the capabilities of traditional planning methods.

3.2.3. Cognitive Architecture of the Synergistic Sequencing Method

We propose a synergistic sequencing framework that implements computational path-dependency analysis to capture the evolutionary dynamics of expressway networks (Figure 2). This cognitive architecture conceptualizes infrastructure planning as a dynamic topological optimization problem where each construction decision reconfigures the network's state space, creating bifurcation points that constrain subsequent evolutionary trajectories.

The decision support framework begins with temporal stratification of Chongqing's expressway planning projects (2023–2035) into three distinct phases (Phase 1, Phase 2, and Phase 3), reflecting their prioritization in official planning documents. Within each phase, our system implements an iterative evaluation process that systematically explores how individual projects modify the network topology when integrated into the existing infrastructure.

The core innovation of our approach lies in treating construction sequencing as an emergent property arising from iterative network reconfiguration. Rather than evaluating projects as static entities with fixed attributes, our decision support framework dynamically reassesses each candidate project's network-wide impact after every construction decision, capturing how topological modifications propagate through the system. This process continues until all projects within a phase are sequenced, before advancing to subsequent phases, ensuring consistency with administrative planning horizons while optimizing topological evolution within each development stage.

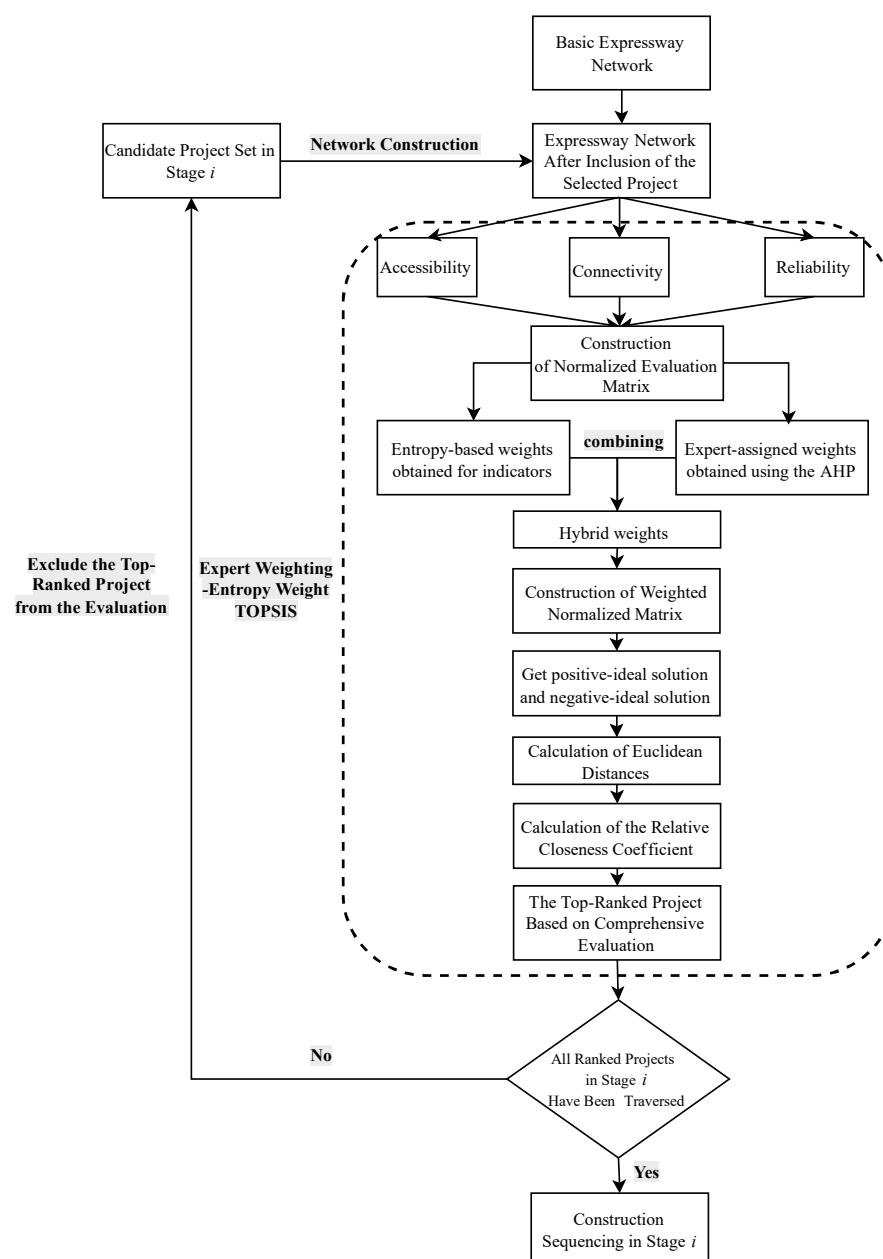


Figure 2. The framework of the synergistic sequencing method.

To elucidate the proposed method's execution process and decision-making steps, this study presents an analysis using three expressway lines as examples. Based on the existing road network, the impacts of three distinct scenarios (A, B, and C) on the network state are simulated. The simulation results yield data for three dimensions with nine indicators, as shown in Table 3. The mixed weights for each indicator are calculated by combining entropy-based and expert-assigned weights, as shown in the table below.

Table 3. Expressway network evaluation in the first iteration.

Dimension	Indicator	Line A	Line B	Line C	Hybrid Weight
Accessibility	Network Coverage Ratio	0.5502	0.5772	0.5739	0.1027
	Network Density	2.1275	2.1500	2.1564	0.1037
	Detour Ratio	2.0830	2.0819	2.0816	0.1036
Connectivity	Connectedness	1.5077	1.4776	1.4862	0.1302
	Average Path Length	59.4751	59.8522	60.1111	0.1179
	Clustering Coefficient	0.3746	0.3746	0.3746	0.0333

Small-World Coefficient	1.4232	1.3476	1.4132	0.1028
Betweenness Centrality	0.04675	0.04623	0.04700	0.1056
Robustness	6.1920	6.1876	6.3565	0.2002
T_i	0.4469	0.3565	0.6649	

According to the computed relative closeness coefficient T_i , Line C is identified as the preferred candidate for priority construction. Although Line A performs strongly in terms of small-world characteristics and average path length, thereby offering higher network travel efficiency, Line C demonstrates more pronounced overall advantages across several critical indicators, including robustness, betweenness centrality, and network density. In particular, with robustness carrying the most significant hybrid weight (0.2002), Line C markedly outperforms the other alternatives, indicating that its incorporation would substantially enhance the network's resistance to disruptions and structural failures. By contrast, Line A can be characterized as an efficiency-oriented project, whose primary contribution lies in reducing system-wide path distances and, consequently, improving traffic circulation efficiency. If decision priorities emphasize operational efficiency over resilience, Line A's relative standing could be improved by appropriately recalibrating the expert-derived weights (e.g., assigning greater importance to average path length). Nevertheless, under the current weighting scheme, Line A ranks second. Line B exhibits comparatively moderate performance in this evaluation. However, it achieves a higher network coverage ratio; its contribution to topological enhancement (e.g., connectivity and small-world properties) is weaker than those of Lines A and C, resulting in a third-place ranking. Overall, based on the present analysis, Line C should be prioritized for integration into the expressway network.

Based on the second-iteration evaluation results presented in Table 4, the relative closeness coefficient T_i indicates that Line A achieves a score of 0.634, substantially higher than Line B (0.366); therefore, Line A ranks first in this iteration. A further comparison of indicator-level contributions shows that, although Line B has a slight advantage in network coverage ratio and network density, Line A exhibits a lower detour ratio, a shorter average path length, higher connectedness, a small-world coefficient, and superior robustness and betweenness centrality. In addition, the clustering coefficient is identical for both alternatives, and its weight is set to zero in this iteration; accordingly, it provides no discriminative power and has no material impact on the final ranking. Synthesizing the evaluation outcomes across the two iterations, the overall priority order of the three candidate lines is Line C, Line A, and Line B.

Table 4. Expressway network evaluation in the second iteration.

Dimension	Indicator	Line A	Line B	Hybrid Weight
Accessibility	Network Coverage Ratio	0.5850	0.5951	0.1250
	Network Density	2.1400	2.1802	0.1250
	Detour Ratio	2.0501	2.1043	0.1250
Connectivity	Connectedness	1.5200	1.4900	0.1250
	Average Path Length	58.1000	59.9002	0.1250
	Clustering Coefficient	0.3746	0.3746	0.0000
	Small-World Coefficient	1.4504	1.3600	0.1250
Reliability	Betweenness Centrality	0.04878	0.04650	0.1250
	Robustness	6.4501	6.2500	0.1250
	T_i	0.6340	0.3660	

To assess the accuracy of the different measures, we use the Kendall correlation coefficient to measure consistency between two rankings (i.e., the ranking list from the decision support method and the ground-truth ranking list generated from the actual construction schedule arrangement for expressway projects). Let R^μ be the rank vector of a measure μ and R^a be the rank vector of the actual construction schedule. The rank correlation τ is defined as follows:

$$\tau(R^\mu, R^a) = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}, \quad (32)$$

where n_c and n_d represent the numbers of concordant and discordant pairs, respectively, and n_0 is equal to $n^s(n^s - 1)/2$, where n^s is the size of the ranking list. $n_1 = \sum_i t_i(t_i - 1)/2$, $n_2 = \sum_j u_j(u_j - 1)/2$, where t_i is the number of tied values in the i_{th} group of ties and u_j is the number of tied values in the j_{th} group of ties. The value of τ ranges from -1 to 1 . A higher τ value means greater accuracy of the method τ , whereas a low value indicates dissimilarity. Using the three expressway lines case as an example, if the actual construction schedule ranking R^a is also Line C, Line A, and Line B, then $\tau(R^\mu, R^a) = 1$. This result indicates that the ranking produced by the synergistic sequencing method is perfectly consistent with the ground-truth construction order.

4. Decision Support Framework Validation and Path-Dependent Network Evolution Analysis

This section presents the comprehensive validation and analysis of our decision support system through application to real-world expressway planning in Chongqing. We demonstrate how our approach captures complex path-dependent dynamics and emergent network properties that conventional planning methods fail to identify.

4.1. Computational Intelligence Application to Expressway Network Evolution

4.1.1. Knowledge-Based Phase Analysis of Chongqing Expressway Development

The Chongqing Expressway Network Plan (2023–2035) presents an ideal test case for our decision support framework, as it represents a complex system intervention aimed at transforming network topology through strategic infrastructure development. The plan proposes a sophisticated final configuration comprising four ring expressways, 22 radial routes, and 60 connecting lines, totaling 8500 km.

To analyze this evolutionary process, our decision support framework employs a temporal stratification approach that aligns with official planning horizons, enabling systematic analysis of emergent network properties. Table 5 presents the distribution of projects across these temporal phases, demonstrating the substantial scale of this infrastructure intervention.

Table 5. Knowledge representation framework for phase-based expressway network evolution.

Phase	Projects	Length (km)	Investment (RMB Billion)	Land (ha)	Implementation
Phase 1	17	656	994	60,662	2016–2025
Phase 2	12	864	1730	89,090	2019–2029
Phase 3	30	1366	2516	145,185	2029–2035

The decision support framework's analysis of spatial project distribution across phases reveals a systematic topological transformation (Figure 3). Phase 1 projects exhibit characteristic preferential attachment patterns, clustering around high-centrality metro-

politan regions while establishing critical long-range connections to peripheral areas (Figure 3b). This computational identification of emergent network patterns aligns with theoretical predictions from complex network science. Phase 2 introduces a strategic topological shift toward balanced regional connectivity (Figure 3c), with our decision support framework identifying the critical cross-regional corridors (Dazhu–Dianjiang–Fengdu–Wulong) that transform the network architecture from radial dominance to a grid-like structure. This transition represents a fundamental shift in network structure, reducing hierarchical dependencies while establishing new functional connections.

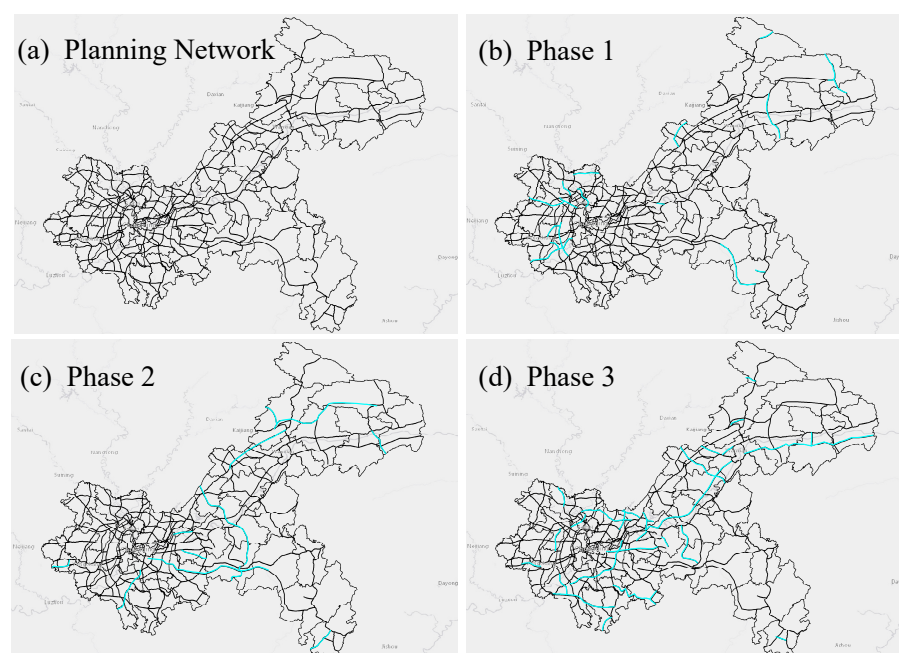


Figure 3. Decision support framework analysis of spatial distribution patterns in Chongqing expressway projects. The blue lines indicate the distribution of expressway projects at different stages.

Phase 3 completes the network transformation through comprehensive grid densification (Figure 3d), with projects distributed evenly across all regions. The decision support framework identifies how this final phase establishes both cross-boundary connections and local network reinforcements, finalizing the transition from a scale-free to a more robust small-world network structure.

4.1.2. Computational Analysis of Emergent Network Properties

Our decision support system quantified the emergent properties of Chongqing's expressway network through the nine intelligent indicators defined in Section 3.2. Table 6 presents the computational analysis of these metrics across development phases, revealing nonlinear dynamics characteristic of complex adaptive systems. It should be noted that the indicator values reported in Table 6 represent the final network-level outcomes after all projects in each development stage have been completed. Subsequent Sections 4.2 further describe, for each development stage, the incremental evolution of the nine indicators as individual projects are implemented sequentially.

Table 6. Decision support framework analysis of topological indicator evolution.

Network Stage	Accessibility				Connectivity		Reliability		
	ω_g	γ_g	Y_g	C_g	$\langle g \rangle$	$\langle C \rangle$	σ_g	B_g	R_g
Current network	0.9473	3.1879	1.8626	2.4613	71.5993	0.2126	1.001	0.0470	6.0076
Phase 1 network	0.9473	3.6375	1.9812	2.8084	79.8611	0.3073	1.4232	0.0461	6.9657
Phase 2 network	0.9473	4.2412	1.8403	3.2745	72.9920	0.2845	1.3476	0.0415	8.0667
Phase 3 network	0.9473	5.1574	1.8226	3.9819	70.7833	0.3125	1.4806	0.0307	10.1782

The decision support framework identified several critical patterns that demonstrate the path-dependent nature of infrastructure sequencing:

Detection of non-monotonic accessibility dynamics: While coverage ratio (ω_g) remains constant at 0.9473 (indicating pre-existing expressway access for most counties), the system detected that density (γ_g) and connectedness (C_g) both increase by 61.8% through the development phases. Most significantly, the decision support framework identified non-monotonic behavior in the detour ratio (Y_g), which initially increases by 6.4% in Phase 1 before ultimately decreasing by 2.1% in Phase 3. This computational detection of non-linear patterns demonstrates how initial network expansion through peripheral connections temporarily reduces efficiency before subsequent grid reinforcement optimizes travel directness—a counterintuitive finding that conventional planning approaches would likely miss.

Identification of emergent small-world properties: The decision support framework detected the emergence of small-world properties through sequential topological modifications. The system identified bifurcation behavior in the average path length ($\langle g \rangle$), which first increases from 71.6 km to 79.9 km (+11.6%) as the network expands spatially, then decreases to 70.8 km (−11.4%) as critical links establish more direct connections. Simultaneously, the system detected substantial increases in both clustering coefficient ($\langle C \rangle$) and small-world coefficient (σ_g) by 47.0% and 47.9%, respectively. This computational identification of small-world emergence, where the network simultaneously enhances both local clustering and global efficiency, represents a critical finding for the optimization of transportation systems.

Computation of topological transformation patterns: The decision support framework’s reliability analysis provides strong evidence of structural transformation from scale-free to more robust configurations. The system detected a decrease in betweenness centrality variance (B_g) by 34.7%, indicating reduced dependency on critical “bridge” edges, while robustness (R_g) increases by 69.4%, reflecting enhanced resilience against both random failures and targeted attacks. Figure 4 visualizes this transformation through the decision support framework’s analysis of edge betweenness centrality distribution, illustrating an evolution from a concentrated state (Figure 4b) to a diffused state (Figure 4c) and finally to an equilibrium state (Figure 4d).

This spatial redistribution of traffic flow centrality, detected by our decision support framework, reflects the network’s structural transition from vulnerable, tree-like configurations dominated by radial corridors to resilient grid patterns with redundant pathways and balanced load distribution. These computational results validate our intelligent approach by demonstrating its ability to detect emergent network properties that go beyond the simple sum of individual links—a critical capability for effective infrastructure planning and design.

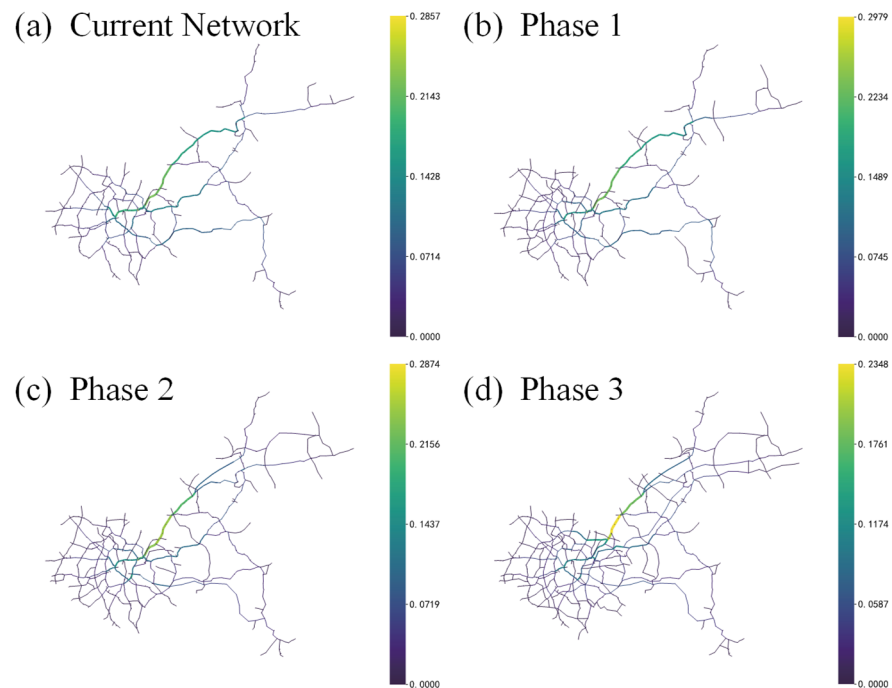


Figure 4. Edge betweenness centrality evolution across development phases.

4.2. Path-Dependent Sequencing Analysis Through Computational Intelligence

4.2.1. Intelligent Topological Prioritization Through Hybrid TOPSIS

We applied our decision support framework to derive optimal construction sequences for Chongqing's expressway infrastructure, implementing the computational framework developed in Section 3.2. The system conceptualized the planning challenge as a phase-based network evolution problem, integrating complex network theory with our hybrid TOPSIS methodology to quantify the cascading effects of sequential construction decisions.

The decision support framework incorporated all nine topological indicators across three functional dimensions—accessibility (ω_g , γ_g , and Y_g), connectivity (C_g , $\langle g \rangle$, $\langle C \rangle$, and σ_g), and reliability (B_g and R_g)—with dimensional weights of 0.33, 0.33, and 0.33, respectively, which were assigned using an equal-weighting scheme since the relative importance among the three dimensions was not explicitly examined in this study. This balanced weighting reflects the equal importance of spatial coverage, efficiency, and resilience in complex infrastructure systems. Rather than applying static prioritization, our approach dynamically reassessed network performance after each construction decision, capturing how earlier choices reconfigure the solution space for subsequent decisions.

The construction sequences that emerged from our analysis reveal a striking example of self-organizing topological evolution, in which each decision creates new structural possibilities that would be inaccessible to static prioritization methods. This path dependency is particularly evident in how early-phase modifications establish fundamental network characteristics that subsequent phases build upon.

4.2.2. Phase 1: Intelligent Detection of Hierarchical Structure Emergence

The decision support framework's analysis of Phase 1 sequencing (Table 7) demonstrates computational detection of preferential attachment mechanisms theorized in complex network science. The system identified an optimal sequence that prioritizes core metropolitan connections (10 of 17 projects), with eight of the top ten projects reinforcing the central urban region.

Table 7. Construction sequencing results of Phase 1 and Phase 2 projects in Chongqing.

Order by <i>HT</i>	Order by <i>EC</i>	Phase 1		Order by <i>HT</i>	Phase 2	
		Actual Con- struction Schedule	Project Information in Phase 1		Project Information in Phase 2	
1	5	2	Nanchuan Western Ring	1	Capacity Expansion of the Chongqing-Hunan Expressway (Banan–Pengshui section)	
2	6	3	Hechuan–Bishan–Jiangjin	2	Chongqing–Chishui–Xuyong	
3	2	1	Capacity Expansion of Yusui (Beibei–Tongliang Section)	3	Wulong–Daozhen	
4	16	4	Hechuan Western Ring	4	Fuling North Ring	
5	1	5	Yuwu Expressway Parallel Line (Beibei–Hechuan)	5	Kaizhou–Liangping	
6	4	6	Yongchuan–Jiangjin	6	Rongchang Southeast Ring Line	
7	7	7	Yongchuan–Bishan	7	Dazhu–Dianjiang–Fengdu–Wulong	
8	12	14	Yunyang Jiangkou–Longgang	8	Wuxi–Yunyang–Kaizhou	
9	17	13	Hechuan Shuanghuai–Qiantang	9	Fengjie–Jianshi	
10	9	12	Kaizhou–Chengkou–Langao (Chengkou–Langao Section)	10	Wulong Pingqiao–Fuling Dashun	
11	10	9	Pengshui–Youyang	11	Wanzhou–Dazhou	
12	3	11	Jiangjin–Luzhou North Line	12	Xiushan–Yinjiang	
13	15	10	Tongliang–Anyue			
14	13	15	Wushan–Wuxi (Dachang–Wuxi Section)			
15	11	14	Liangping–Kaijiang			
16	14	16	Wuxi–Zhenping			
17	8	17	Pengshui–Youyang–Yongshun (Youyang Huatian Tunnel Section)			

Our decision support framework detected how the highest-ranked projects—urban ring roads (Nanchuan Western Ring and Hechuan Western Ring) and inter-county connectors (Hechuan–Bishan–Jiangjin)—create critical structural changes that propagate throughout the network. After implementing just the first four projects, the system measured increases in connectedness (C_g) and density (γ_g), both of which increased by 2.8% (Figure 5b,c), while the detour ratio (Y_g) decreased by 1.7%, demonstrating how targeted topological modifications can generate disproportionate system-wide improvements.

Most significantly, the network exhibits a nonlinear phase transition after the 11th project (Pengshui–Youyang), where the clustering coefficient ($\langle C \rangle$) abruptly jumps from 0.199 to 0.238 (+19.6%). This dramatic inflection point, visualized in Figure 5c, represents a bifurcation in the network's evolutionary trajectory where a single connection triggers emergent clustering properties that transcend local connectivity changes.

Similarly, the small-world coefficient (σ_g) displays non-monotonic behavior, decreasing from 1.001 to 0.940 during the first ten projects before rapidly increasing to 1.423 (+51.4%) with projects 11–16. This qualitative structural transformation from local optimization to global reconfiguration demonstrates how construction sequencing creates path-dependent evolutionary trajectories with phase transitions that cannot be predicted from

isolated project evaluations. The reliability metrics further illustrate these cascading effects. Early ring road construction reduced betweenness centrality deviation (B_g) by 1.3% while increasing robustness (R_g) by 8.3% after just four projects (Figure 5d), demonstrating how strategic topology modifications enhance system-wide resilience through load redistribution mechanisms.

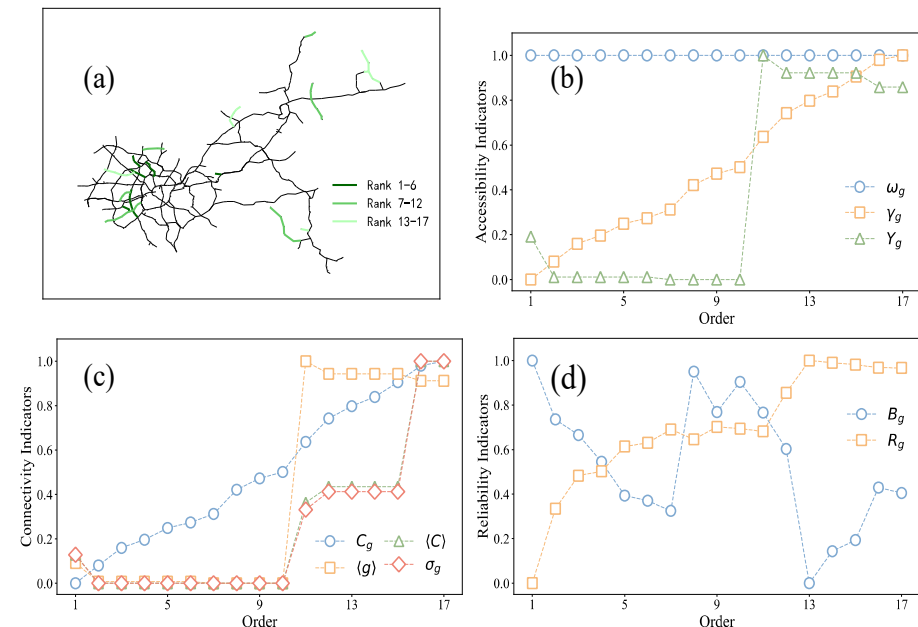


Figure 5. Decision support framework analysis of spatial distribution and indicator evolution in Phase 1. (a) Construction sequence of expressway projects in Phase 1; (b) Evolution of accessibility indicators in Phase 1; (c) Evolution of connectivity indicators in Phase 1; (d) Evolution of reliability indicators in Phase 1.

To demonstrate the effectiveness of the proposed method, we employ the Kendall correlation coefficient to illustrate the superiority of the approach presented in this paper. Correlation analyses are conducted to assess the consistency between the construction sequencing results obtained from the proposed method and EC , denoted as R^{HT} and R^{EC} respectively, and the actual construction sequence R^a . The results indicate that the proposed method exhibits a higher correlation with the actual decision ranking, achieving a value of 0.76 (p -value < 0.05), suggesting that the construction sequence derived from the proposed method demonstrates substantial consistency with the actual construction order. In contrast, the τ_b obtained from EC is relatively low at 0.391 (p -value < 0.05), indicating limited consistency between the expert scoring method's rankings and the actual sequence. Overall, the ranking results obtained from the proposed method demonstrate superior accuracy.

4.2.3. Phase 2: Computational Analysis of Structural Transitions

Phase 2 sequencing (Table 7, Figure 6) exhibits a fundamental shift from preferential attachment to balanced regional integration, with projects distributed more evenly across metropolitan (6), northeastern (4), and southeastern (2) regions. This evolutionary stage represents a critical transition from scale-free to small-world network properties.

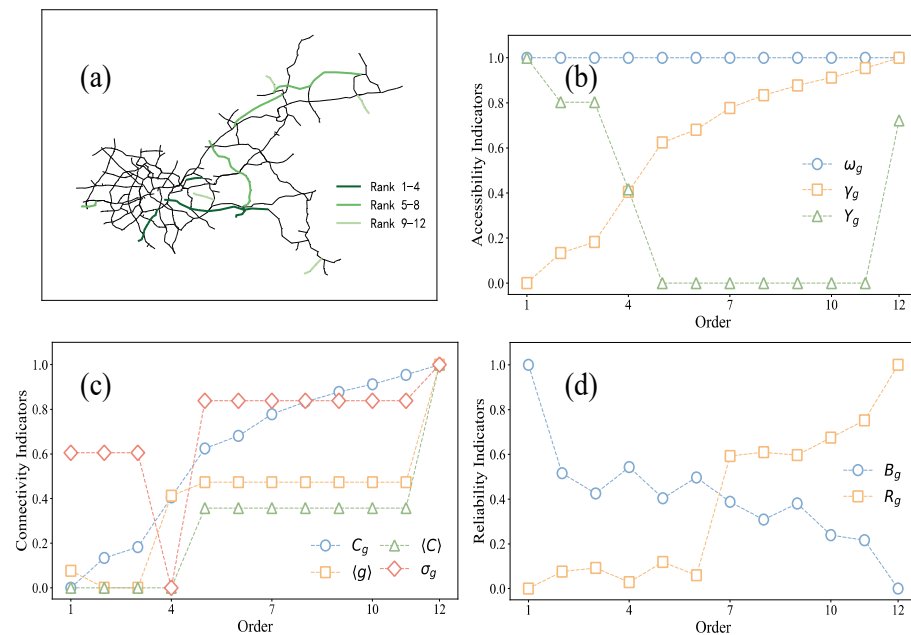


Figure 6. Decision support framework visualization of topological transformation in Phase 2. (a) Construction sequence of expressway projects in Phase 2; (b) Evolution of accessibility indicators in Phase 2; (c) Evolution of connectivity indicators in Phase 2; (d) Evolution of reliability indicators in Phase 2.

The implementation sequence generated significant efficiency improvements, with the detour ratio (Y_g) decreasing by 7.1% (from 1.981 to 1.840) and average path length ($\langle g \rangle$) reducing by 8.6% (from 79.861 to 72.992 km) across the phase (Figure 6b,c). This transformation illustrates how strategically sequenced connections can enhance global network efficiency through targeted local interventions.

The clustering coefficient ($\langle C \rangle$) shows steady growth from 0.272 to 0.285 (+4.8%) while maintaining a high small-world coefficient ($\sigma_g \approx 1.34$), indicating the network's evolution toward mature small-world characteristics that balance local clustering with global efficiency (Figure 6c). This evolutionary pattern confirms the theoretical transition from radial to grid-like topology predicted by complex network theory.

Particularly noteworthy is the implementation of the Dazhu–Dianjiang–Fengdu–Wulong corridor (7th project), which triggered a significant jump in robustness (R_g) from 7.507 to 7.824 (+4.2%) as shown in Figure 6d. This computational detection of a key bifurcation point demonstrates the system's ability to identify how carefully sequenced connections create disproportionate resilience benefits through topological reconfiguration—a capability that conventional prioritization methods lack.

4.2.4. Phase 3: Decision Support Framework Analysis of Network Equilibrium Emergence

The final evolutionary stage (Phase 3) encompasses 30 projects distributed across metropolitan (20), northeastern (9), and southeastern (1) regions, completing the network's transformation toward a resilient grid structure (Table 8, Figure 7). Our decision support framework detected pronounced evidence of network equilibrium mechanisms in this phase, where topological modifications strategically balance load distribution across the system.

The comprehensive coverage increased network density (γ_g) by 21.6% (from 4.241 to 5.157) while reducing betweenness centrality deviation (B_g) by 26.2% (from 0.042 to 0.031), demonstrating how grid densification creates a more balanced flow distribution (Figure 7b,d).

Table 8. Decision support framework’s optimized construction sequence for Phase 3.

Order by <i>HT</i>	Project Information	Order by <i>HT</i>	Project Information
1	Northern Riverside Expressway (Zhongxian–Wanzhou section)	16	Dashi (Hechuan)–Saima (Wusheng)
2	Liangping–Xituo	17	Tuanbao (Changshou)–Shuimotan (Fuling)
3	Yongchuan–Rongchang–Zigong	18	Anwen (Qijiang)–Wenshui (Xishui)
4	Tongliang–Yongchuan Jinlong	19	Baitan (Bishan)–Caojie (Hechuan)
5	Banan–Fuling	20	Youxi (Jiangjin)–Yongxing
6	Sanhe (Fengdu)–Huolu (Wulong)	21	Yubei–Linshui
7	Northern Riverside Expressway (Fuling– Zhongxian section)	22	Liddu–Xinmiao (Fuling West Ring)
8	Wanzhou–Dazhou	23	Xiushan Southern Ring Road
9	Diaojiaba (Jiangjin)–Shuanghekou (Banan)	24	Changshou Branch Phase II
10	Wansheng–Zheng’an	25	Hexi (Nanchuan)–Dayou
11	Jiangdong (Fuling)–Baitao	26	Hechuan–Guang’an–Changshou
12	Hechuan–Beibei–Changshou	27	Wuxi–Fengjie–Yunyang (Fengjie urban section)
13	Jiangjin–Qijiang–Wansheng	28	Chengkou–Xuanhan
14	Fenshui (Wanzhou)–Gaoliang	29	Kaizhou Ring Road
15	Southern Riverside Expressway (Wanzhou–Wushan section)	30	Southern Riverside Expressway (Wushan–Badong section)

Most significantly, our decision support framework identified a critical phase transition after the seventh project (Northern Riverside Expressway, Fuling–Zhongxian section), which produces simultaneous jumps in clustering coefficient ($\langle C \rangle$) (+7.6%, from 0.291 to 0.313), small-world coefficient (σ_g) (+7.3%, from 1.380 to 1.481), and betweenness centrality deviation (B_g) (−7.3%, from 0.041 to 0.038), as shown in Figure 7c,d. This computational detection of a “tipping point” demonstrates the decision support framework’s ability to identify how strategically positioned connections trigger system-wide reorganization, creating central axes that fundamentally reconfigure flow patterns throughout the network.

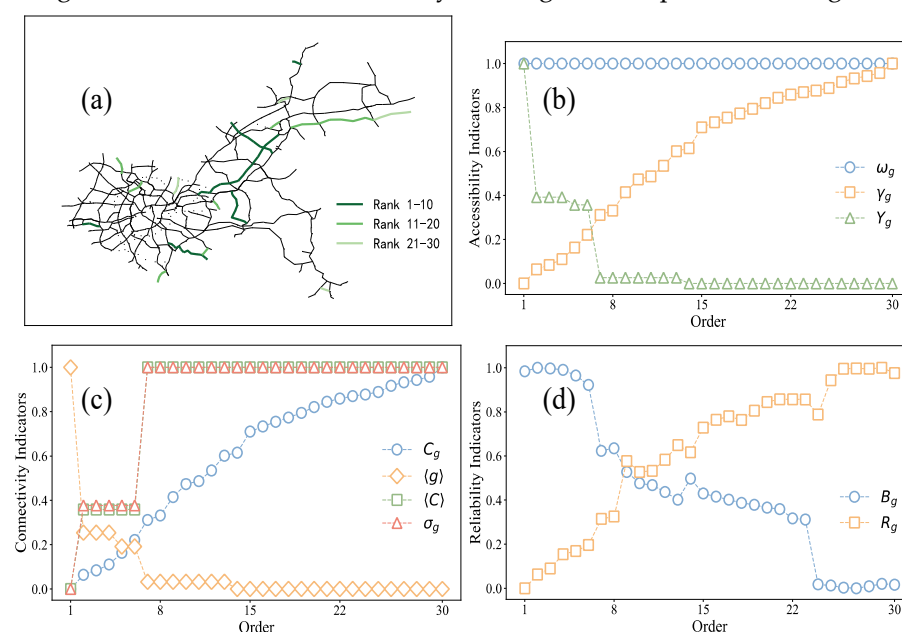


Figure 7. Decision support framework analysis of network equilibrium emergence in Phase 3. (a) Construction sequence of expressway projects in Phase 3; (b) Evolution of accessibility indicators

in Phase 3; (c) Evolution of connectivity indicators in Phase 3; (d) Evolution of reliability indicators in Phase 3.

The decision support framework further detected optimization patterns in network structure, with average path length ($\langle g \rangle$) decreasing by 8.1% (from 77.017 to 70.783 km) and connectedness (C_g) increasing by 20.7% (from 3.300 to 3.982). These computational findings reflect the decision support framework's ability to identify network transitions that lead to mature grid structures with balanced flow distribution and multiple redundant pathways—characteristics that emerge from the cumulative effects of sequentially implemented topological modifications.

4.3. Computational Intelligence Insights for Infrastructure Planning

Our decision support framework's analysis reveals three fundamental principles of infrastructure network evolution that conventional planning approaches typically miss:

- I. Phase-specific topological transitions: The decision support framework identified distinct evolutionary patterns across development phases—preferential attachment in Phase 1 (reinforcing high-centrality nodes), balanced regional integration in Phase 2 (creating cross-regional corridors), and grid densification in Phase 3 (establishing redundant pathways). This computational detection of structural transformation patterns demonstrates how intelligent sequencing decisions can strategically guide network evolution toward desired functional characteristics.
- II. Nonlinear performance dynamics: Our decision support framework detected non-monotonic behavior in network performance indicators, characterized by temporary degradation followed by dramatic improvements after critical thresholds are crossed. These computational identifications of phase transitions, particularly evident in clustering coefficient and small-world properties, demonstrate how complex adaptive systems reorganize through discrete evolutionary jumps rather than gradual, linear improvements, a critical insight for effective infrastructure planning.
- III. Bifurcation-driven path dependency: The decision support framework's simulation capabilities revealed how each construction decision creates bifurcation points that fundamentally alter subsequent evolutionary possibilities. The computational identification of these path dependencies confirms that construction order, not merely project selection, determines system performance—a finding with significant implications for transportation planning authorities.

These computational findings validate our decision support framework by demonstrating its ability to capture emergent properties in infrastructure evolution that cannot be predicted through conventional project-by-project evaluation. The decision support framework's detection of transitions from radial to grid structure, accompanied by corresponding improvements in efficiency and reliability, demonstrates how computational intelligence can guide infrastructure planning toward desired functional characteristics.

By conceptualizing expressway construction as a sequence of topological modifications within a complex adaptive system, our decision support framework provides transportation authorities with previously unavailable decision intelligence—enabling the strategic transition from vulnerable tree-like structures to resilient small-world configurations through carefully orchestrated modification sequences that conventional planning approaches cannot identify.

5. Conclusions and Future Directions

5.1. Advancing Decision Support Intelligence for Infrastructure Planning

This research advances decision support framework applications by reconceptualizing infrastructure sequencing as a complex adaptive system problem. By integrating computational intelligence with network science, we developed a knowledge-based decision support framework that captures the nonlinear evolutionary dynamics and emergent properties of expressway networks. Our decision support framework addresses three fundamental limitations in conventional infrastructure planning: fragmented evaluation perspectives [36], static optimization frameworks [37], and linear aggregation methodologies [38].

The decision support framework's core innovation lies in its path-dependent computational reasoning, operationalized through a hybrid expert-entropy-weighted TOPSIS methodology that dynamically reassesses project priorities after each topological modification. Unlike conventional decision support systems, which treat infrastructure components as static entities, our approach performs computational simulations of network evolution via phase transitions and bifurcation points. This reveals how topologically equivalent construction decisions produce dramatically different system-wide outcomes depending on implementation sequence—a critical insight for infrastructure planning that traditional frameworks cannot provide.

Empirical validation using Chongqing's expressway planning (2023–2035) demonstrates the decision support framework's ability to identify three distinct evolutionary patterns: Phase 1: Preferential attachment dynamics through metropolitan reinforcement, significantly enhancing clustering coefficient (+44.56%) and small-world properties (+42.2%); Phase 2: Balanced regional integration through cross-regional corridors, reducing average path length (−8.6%) and detour ratio (−7.1%); Phase 3: Grid densification effects that decrease betweenness centrality variance (−26%) while increasing robustness (+69.4% overall).

These computational findings confirm theoretical predictions from complex systems science: transportation networks evolve from vulnerable, tree-like configurations into resilient small-world structures through strategic topological modifications, rather than merely through capacity expansion. The identification of critical tipping points—such as the Northern Riverside Expressway (Fuling–Zhongxian section)—demonstrates the system's unique capability to detect nonlinear dynamics that conventional planning tools miss.

5.2. Methodological Innovations to Decision Support Frameworks

The knowledge-based system developed in this research transcends traditional infrastructure planning approaches through four methodological innovations:

- I. Topological knowledge representation: Our system implements a knowledge representation framework that analyzes how construction decisions modify emergent network properties rather than treating projects as isolated components. This enables a comprehensive assessment of system-wide impacts that surpasses the capabilities of traditional evaluation methods.
- II. Evolutionary dynamics simulation: The system captures network evolution through iterative topology reassessment algorithms, simulating how infrastructure networks evolve through discrete phase transitions rather than linear improvements. This computational capability reveals emergent properties that conventional planning approaches cannot detect.
- III. Hybrid knowledge fusion mechanism: Our decision support framework integrates qualitative domain expertise with quantitative network science through an adaptive

weighting mechanism that balances human judgment with entropy-based uncertainty quantification. This addresses the fundamental uncertainty inherent in evaluating complex systems, providing more robust decision support.

- IV. Vulnerability analysis intelligence: The system incorporates advanced network vulnerability analysis through topological reliability metrics, identifying critical infrastructure elements whose modification disproportionately enhances system-wide resilience. This capability enables proactive planning for robust infrastructure development.

These methodological contributions collectively enable transportation authorities to implement evidence-based sequencing strategies that exploit structural synergies beyond the capabilities of traditional planning methods. By computationally simulating how networks evolve through phase transitions and bifurcation points, our decision support framework provides strategic infrastructure development decision support that conventional approaches cannot offer.

5.3. Limitations and Future Research Directions

Despite its significant advances in computational intelligence, three limitations constrain the current implementation: I. Static topological representation: The current system emphasizes network structure rather than dynamic traffic flow patterns, potentially overlooking temporal variations in system behavior. II. Limited uncertainty quantification: The decision support framework incorporates uncertainty via entropy-based weighting but has limited capabilities to model exogenous factors, such as construction delays and disruption events. III. Simplified constraint modeling: The current implementation treats administrative phasing as fixed rather than as variables within a more comprehensive optimization framework.

These limitations suggest three promising directions for future research: Machine learning techniques can be integrated with our network science framework to develop more sophisticated decision support systems that can learn from historical patterns of infrastructure evolution. Deep reinforcement learning algorithms could be trained on historical network development data to identify optimal evolutionary trajectories under various constraints. Temporal graph neural networks would enable modeling of time-dependent network dynamics, capturing how usage patterns evolve in response to structural modifications—significantly improving sequencing optimization based on both structural and functional characteristics. Future implementations should incorporate advanced uncertainty modeling through Bayesian networks and multi-scenario simulation. This enhancement would enable more robust sequencing recommendations that account for the inherent unpredictability of infrastructure development. Monte Carlo simulation techniques integrated with path-dependent analysis would generate probability distributions of performance outcomes under various sequencing scenarios, enabling transportation authorities to identify strategies that perform well across multiple possible futures. The next generation of our decision support system should integrate explainable AI techniques that make complex path-dependency concepts accessible to transportation planners. Interactive visualization tools with integrated explanation capabilities would enhance practical utility by allowing stakeholders to understand the reasoning behind sequencing recommendations. Knowledge graph technologies could represent relationships between infrastructure components, evolutionary trajectories, and performance outcomes, enabling intuitive exploration of topological possibility spaces.

5.4. Practical Implications

This research fundamentally transforms infrastructure planning practice by demonstrating the critical importance of intelligent sequencing. The application of our decision

support framework to Chongqing's expressway network reveals that construction order, not merely project selection, determines the ultimate system performance—a finding with profound implications for transportation authorities worldwide.

By conceptualizing expressway development as an evolutionary process characterized by path dependence and phase transitions, our decision support framework provides both theoretical insights into network growth dynamics and practical guidance for infrastructure planning. The demonstrated transition from radial to grid-like structures through strategically sequenced modifications confirms that network evolution trajectories, not merely final configurations, determine system performance.

The practical value lies in the system's ability to identify non-obvious sequencing strategies that maximize synergistic network effects. By implementing the computational intelligence principles demonstrated in this research, transportation authorities can achieve significantly higher system performance from the same set of projects through optimized sequencing—a capability particularly valuable in resource-constrained environments where maximizing return on infrastructure investment is critical.

In conclusion, this research advances decision support frameworks for infrastructure planning by bridging complex network theory with practical decision-making. Our computational approach reveals how carefully orchestrated sequencing strategies can guide network evolution toward optimal topological configurations that balance accessibility, connectivity, and reliability, providing a foundation for next-generation planning support systems that can navigate the complex challenges of sustainable infrastructure development.

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