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Research on a Model of Node and Path Selection for Traffic Network Congestion Evacuation Based on Complex Network Theory

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ABSTRACT Based on relevant complex network theory, this paper analyzes the characterization parameters of traffic network complexity, such as the causes of traffic congestion and evacuation models. From the perspective of the traffic capacity of traffic network nodes, combined with the transit time of each road, model is proposed for selecting the weights of congestion evacuation nodes. According to the evacuation target, combined with characteristic parameters, such as node degree, node strength, clustering coefficient and closeness, the grey system evaluation method and the analytic hierarchy process (AHP)are combined. Based on the grey relational analysis model, a model is established for determining the priority connectivity evaluation value of each node. The complex characteristics of the actual traffic network in the Chaoyang District of Changchun City are analyzed, then the selection weights of each node of the traffic network are obtained. Having defined the distance between complex network nodes, a congestion evacuation path selection model is proposed, and an evacuation path scheme is given for specified start and end points.

INDEX TERMS Traffic network complexity, traffic flow, selection weight, priority connectivity, grey relational analysis, prediction, modeling and simulation.

I. INTRODUCTION

Traffic congestion usually occurs in situations, such as: morning and evening peaks, extreme weather conditions, etc. A good evacuation strategy can effectively avoid road and node traffic congestion caused by the rapid influx of vehicles, and restore traffic to normal levels as soon as possible. Common evacuation strategies are divided into individual optimal and system optimal. The former aims to achieve the shortest trip or the shortest time, while the latter aims to achieve the lowest total cost of travel within the system. Cova *et al.* [1] studied the shortest path evacuation strategy based on road topology; Yamada [2] proposed the shortest path retreat method, minimizing the total cost of all evacuations. The existing strategy only considers a single target of the shortest path or smallest amount of time, obtaining the optimal result, which has a long operation time and low efficiency.

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Exploring the complexity of a traffic network is beneficial as it can be provided a more accurate assessment of traffic network characteristics. It is important to select evacuation nodes and paths based on these characteristics evacuation in the event of congestion, to save on computational steps and improve efficiency.

In recent years, many scholars have come up with many practical theories and methods for applying complex network theory to evacuation in the case of traffic congestion.

Sienkewicz *et al.* studied the topological structure of public traffic networks in major cities in Poland, and calculated the dielectric properties and clustering coefficients of traffic networks [3]–[5]. In 2006, Angeloudis *et al.* studied the complex characteristics of subway networks in New York and Paris, and constructed an evolution model to simulate the evolution process of the subway network [6]. Montis constructed a traffic network that reflected the traffic relations between major Italian cities, focusing on the correlation between traffic volume and topology in the traffic network. In 2004, Ziyou Gao *et al.* gave a theory of balanced distribution of traffic networks, studying the scale characteristics of Beijing's public traffic network, and analyzing the distribution characteristics of the network [7]. Changxi Ma *et al.* analyzed the impact of aggressive driving behavior and path optimization in taxi carpooling on congestion generation and evacuation [8]–[9]. In 2009, Tao Wang carried out the evolution of Space L and Space P for an actual traffic network, proposed route selection connection and a random walk mechanism for congestion station, calculated the degree distribution, clustering coefficient and average path length, and constructed an evolution model [10]. From the perspective of urban loop road traffic control, Changxi Ma *et al.* applied a two-way parallel catastrophe particle swarm algorithm to form a pre-selection scheme and effectively reduce delays and congestion [11]. In 2013, Jiaorong Wu *et al.* proposed to use the modified line median centrality index to extract the main paths, ignoring the weight consideration of the traffic network [12].

In order to avoid the impact of traffic congestion on urban traffic operations, this paper aims to propose a congestion evacuation solution. Based on the complex characteristics of the traffic network, first, the traffic capacity of the node and the transit time of the path are combined, to propose a model for selecting the node weights for path selection in the traffic network. Second, the complex characteristics of traffic network nodes are studied. According to the evaluation objectives, the grey system evaluation method and the AHP are combined. Based on the grey relational analysis model [13], a priority connectivity evaluation value model is established. Finally, based on the definition of the distance between traffic network nodes, a congestion evacuation path selection model is constructed under the condition that the weights of the nodes are known.

The model for selecting the evacuation node weights comprehensively considers the local and global characteristics of the traffic network nodes. It has selected the local characteristics parameters, including node degree and node strength of the traffic network, then selected the global characteristic parameters, including clustering coefficient and closeness. These characteristic parameters not only fully consider the actual topology, but also highlight the important nodes. Moreover, the impact of the actual traffic volume of the traffic network on the connectivity of the nodes is considered through the strength parameters, and the node traffic capacity that is able to participate in the evacuation.

II. TRAFFIC NETWORK CONGESTION EVACUATION NODE AND PATH SELECTION MODEL

When congestion occurs in a traffic network, the nodes and paths of the evacuation process must be based on the transit time of the evacuated paths, and the traffic capacity of the evacuated nodes. A traffic network is a kind of complex network. We can consider which nodes and paths to choose from the perspective of the complex network in order to solve the problem of traffic congestion.

A. THEORETICAL BASIS OF COMPLEX NETWORKS

The urban traffic network studied in this paper refers to a network composed with infrastructure such as intersections and roads. During the research process, this paper abstracted the traffic network into a network with a certain topology. In this paper, signal-controlled intersections are abstracted as nodes, and roads between intersections are abstracted as edges. Then, the traffic network can be abstracted into a graph G = (N, E), while N = nodes, E = edges.

The well-known Chinese scientist Qian Xuesen, proposed the current definition that: complex networks are self-organizing, and have self-similarity, attractors, small worlds, and some or all scale-free characteristics [14].

Complex networks can be divided into three basic network topologies: (1) regular networks, (2) random networks, and (3) small world and scale-free networks. The main basis for distinguishing between these three topologies is by means of their distribution, namely the degree distribution, the average path length (AVL), and the clustering coefficient (CC) [15]–[16].

B. NETWORK CHARACTERISTIC PARAMETERS

1) DEGREE DISTRIBUTION

Define the degree k_i of node i, k_i to be the sum of all sides connecting node i. The degree indicates the importance of the node in the network. The degree distribution function $p(k)$ of the network node represents the probability that the degree of the node is k. Common degree distributions are the Poisson distribution and the power law distribution. The node degree distribution reflects the network characteristics. The average node degree is:

$$\langle k \rangle = \frac{1}{N} \sum k_i \tag{1}$$

2) AVERAGE PATH LENGTH

Define the distance d_{ij} between two nodes i and j as the number of edges to travel between the two nodes.
The average path length L is defined as:

$$L = \frac{2}{N(N-1)} \sum\nolimits_{i \ll j} d_{ij} \tag{2}$$

The average path length reflects the degree of separation of the network nodes.

3) CLUSTERING COEFFICIENT

Suppose there are k_i nodes in the network connected to node i, and at most $\frac{k_i(k_i-1)}{2}$ lines between the k_i nodes, and that the actual number of lines is E_i. Then the clustering coefficient of node i is defined as:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{3}$$

The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. Since formula (3) defines the clustering coefficient of the node, it can quantify the closeness between the neighboring nodes connected to node i.

C. COMMON NETWORK TOPOLOGY

1) REGULAR NETWORK

A regular network is the most common basic form of a complex network. The structure of the rule network is relatively simple. Common forms include: globally coupled complex networks, nearest neighbor coupled complex networks, star-coupled complex networks, etc. However, these methods are ideal structural forms, so these networks are uncommon in real networks. The complex characteristic parameters are shown in the following TABLE 1.

TABLE 1. Comparison of common regular network characteristic parameter values.

	AVL	C
Globally coupled network	$L_{gc}=1$	$C_{gc}=1$
Nearest-neighbor coupled network	$L_{nc}=\frac{N}{2K}\to\infty$	$C_{nc}=\frac{3(K-2)}{4(K-1)}\approx\frac{3}{4}$
Star coupled network	$L_{sc}=2-\frac{2(N-1)}{N(N-1)}\to 2$	$C_{CC}=\frac{N-1}{N}\to 1$

2) RANDOM NETWORK

The random network was first proposed by Erdős and Rényi, so it is also called ER model [17]–[18].

It is assumed that the network initially has N isolated nodes, each connecting to any other node in the network with the same probability p, and finally generates a random graph network with N nodes and random lines.

Expected number of lines:

$$\langle L\rangle = \frac{pN(N-1)}{2} \tag{4}$$

Average node degree value:

$$\langle k\rangle = p(N-1)\approx pN \tag{5}$$

The ER random network characteristic parameter values show that the network has typical small-world characteristics when the random network scale is large enough. In the actual network, the network characteristic parameter values are close to the values in the table due to the network size and p value.

When the fixed averaging value is constant, the ER random network can be deduced from the topological structure. Each edge is independent, and the degree distribution can be approximated by the Poisson distribution. When $\lambda=\langle k\rangle$.

$$p(k)=\binom{N}{k}p^k(1-p)^{N-k}\approx\frac{\langle k\rangle^k e^{-\langle k\rangle}}{k!}=\frac{\lambda^k e^{-\lambda}}{k!} \tag{6}$$

When N is infinite, the equation is exactly established. However, in the actual network, the network size is limited, and the degree distribution trend is mostly similar to the Poisson distribution.

TABLE 2. ER random network characteristic parameter values.

	AVL	C
ER random network	$L_{ER}\propto\frac{\ln N}{\ln\langle k\rangle}$	$C_{ER}=p=\frac{\langle k\rangle}{N}<<1$

3) SMALL-WORLD AND SCALE-FREE NETWORK

A large number of physically existing networks, such as computer networks, power networks, and interpersonal networks, are neither strictly regular nor completely random, with specific statistical characteristics. One type has a small-word effect. In 1998, Watts and Strogatz established the WS small-world network model. Later, Newman and Watts proposed the NW small-world model with large clustering coefficients and a short average path length [15]–[16]. One type has scale-free characteristics, and the degree distribution of small-world networks is similar to the pendulum type of distribution. In 1999, Barabási and Albert proposed that the degree distributions of many large-scale complex networks in reality belong to the scale-free power law distribution, $p(k)\sim k$, where k is in the range (2,3) [19].

D. NODE COMPLEX CHARACTERISTIC PARAMETERS

1) CLOSENESS

In a weightless network, the closeness is used to characterize the easy with which one node in the network can reach other nodes [12]:

$$B(i)=\left[\sum_{j=1}^{N}d_{ij}\right]^{-1} \tag{7}$$

The closeness of a node is a measure of centrality in a network. Thus, the more central a node is, the closer it is to all other nodes.

Massimo *et al.* proposed a new concept, the connectivity length D, based on the characteristics of six-degree separation, that gives harmony to the whole theory. The connectivity length D can be evaluated on a global or on a local scale. Moreover, it can be computed not only for the topological cases but also for any metrical network [20]. Dekker proposed the concept of distance in social network analysis [21]. Those concepts and the concept of closeness have similarities.

2) NODE STRENGTH

In a right-weighted network, the weight value of the edge between the connected nodes i and j is defined. The node strength S_i of node i can be defined as the sum of the weights of all the lines associated with node i [12].

Node strength is an important node characteristics, the expression is in formula 8 as follows: q is the actual traffic flow of the road section, c is the actual capacity of the road section.These are two important parameters when describing the edge weight of the network.

The node strength reflects the influence of the local traffic conditions on the node evacuation ability. The node strength, given weights of each side: $\varphi_{ij} = 1 - q/c$,is given by:

$$S_i = \sum\nolimits_{j \in N_i} a_{ij}\varphi_{ij} \tag{8}$$

If there is a connection between i and j,$a_{ij} = 1$, otherwise $a_{ij} = 0$.

This parameter has important reference for the selection of network attack nodes. There are some examples as bellow.

Bellingeri *et al.* found that weighted node attack strategies (deleting them based on the strength of the nodes) most effectively corrupt the system when evaluating weighted nodes efficiency. They use both classic binary node attributes and network function metrics, and then introduce a weighted level of node importance [22].

Bellingeri *et al.* analyzed the response of real-world and model networks, then analyzed the node loss accounting for link intensity and the weighted structure of the network. They used both classic binary node properties and network functioning measure, proposed a weighted rank for node importance (node strength), and used a measure for network functioning that accounts for the weight of the links (weighted efficiency) [23].

3) OTHER RESEARCH RESULTS

This paper applies complex network theory to analyze the characteristics of the network nodes in Changchun City. There are thousands of scholars using network theory to analyze transport and road networks. Among the many papers, there are some achievements that will help future research.

Yu Yang *et al.* analyzed the urban taxi transport network in Xi'an city, based on the GPS trajectory data of taxis, a kind of urban trip complex network was constructed.

They applied some important parameters that reflect the complex network characteristics of the taxis, such as clustering coefficient, average shortest path, vertex intensity, network density, and K-core indexes. Then in this paper, they analyzed the topological properties and geographical characteristics. The results revealed that the interaction relationship between spatial differentiation of taxi trip trajectory network and the topology structure [24].

Bellingeri *et al.* analyzed the response of a complex weighted network based on the Beijing urban road system, and proposed the nodes removal strategies that considered the links weight [25].

Erath *et al.* surveyed the development of the Swiss road and railway transportation network during the recent years, then founded that previously established complex network evaluation criteria do not apply to all networks. It needed to fulfill the requirements and evaluation criteria of some spatial networks. New approaches were applied to distinguish basic network characteristics, such as local network densities and network topology.Then the proposed measures are able to characterize the growth characteristics of Swiss road transportation network [26].

Bono *et al.* proposed a research of flow and path-dependency of the directed weighted networks. They have studied the path-dependencies in closed trails in some metro Politian areas in England and the USA. They computed the global and spatial correlations with measured traffic flows. Then the result shows that the heterogeneous distribution of the traffic intensity has mirrored by the distribution of agglomerate process path dependency. Those high traffic roads are selected along short-to-medium length scale ways in the ensemble of nodes [27].

E. MODEL FOR NODE SELECTION WEIGHTS IN A CONGESTION EVACUATION SCENARIO

In the past, the principle of traffic flow allocation was studied, and single-target factors were considered, preventing smooth flow in the overall network. Therefore, in establishing a congestion evacuation model, path selection should not only consider the transit time of the road, but also the characteristics of the evacuation priority connectivity of the node, to improve traffic evacuation. Evacuation nodes tend to be selected on good traffic capacity and short transit times. Therefore, if node i is congested, the model for the selection weight for connected node j is as follows:

$$Z_{ij} = \gamma R_j + (1-\gamma)(1-T'_{ij}) \tag{9}$$

$$T_{ij} = T^0_{ij}\left[1+\alpha(q/c)^\beta\right] \tag{10}$$

and the local optimal evacuation node selection is:

$$M = \max Z_{ij} \times \xi \tag{11}$$

where Z_{ij} is the selection weight of node j,R_j is the priority connectivity of node j,T_{ij} is the transit time of road section (i, j) when traffic flow is q, and according to the BPR function, T^0_{ij} is the free driving time on road section(i, j),T'_{ij} is the normalized T_{ij},γ is a coefficient, with recommended value 0.7, to reflect the importance of the node characteristics, q is actual traffic flow, c is the actual capacity of the road section, and α, β are coefficients, with recommended values of $\alpha = 0.15$, $\beta = 4$.

Normalized formula:

$$T'_{ij} = \frac{T_{ij} - \min T_{ij}}{\max T_{ij} - \min T_{ij}} \tag{12}$$

Analyzing the relationship between traffic saturation (q/c) and transit time(T_{ij}/T^0_{ij}), the following graph can be drawn according to formula (10):

As can be seen from TABLE 3, in order to keep the flow of traffic within guidance limits, the saturation should be kept below 0.9 as much as possible.

F. ESTABLISHING A MODEL FOR THE NODE PRIORITY CONNECTIVITY EVALUATION

1) STRUCTURAL CHARACTERISTIC PARAMETER EVALUATION MATRIX

This paper combines several static and dynamic evaluation indicators to measure the priority connectivity degree of the

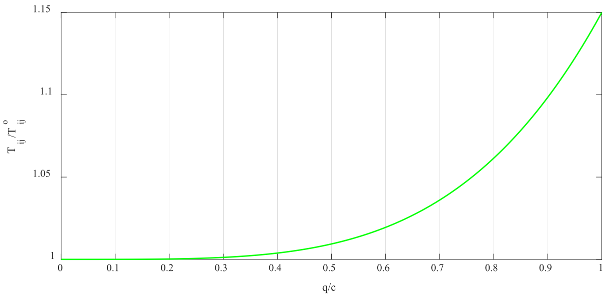

FIGURE 1. Relationship between q/c and T_{ij}/T_{ij}^{0}.

TABLE 3. Urban road service level allocation.

Service level	Traffic	Characteristic description
A	≤ 0.4	Smooth traffic flow, basically no delay
B	≤ 0.6	Stable traffic flow with a small amount of delay
C	≤ 0.75	Stable traffic flow, with some delay
D	≤ 0.9	Close to unstable traffic flow, with a big delay
E	≥ 0.9	Unstable traffic flow, with heavy traffic, and delays

nodes. According to the grey correlation degree model [10], the method of the priority connectivity evaluation value is established. Assuming there are n nodes in the traffic network and j characteristics of the road network, the j indicators of the node i are denoted by $x_1, x_2, \ldots, x_j$.
Then, we can construct the matrix as follows:

$$X_{ij} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1j} \\ x_{21} & x_{22} & \ldots & x_{2j} \\ \ldots & \ldots & \ldots & \ldots \\ x_{n1} & x_{n2} & \ldots & x_{nj} \end{bmatrix} \tag{13}$$

Considering the complex characteristic parameters of the nodes, we select $j = 4$ characteristic parameters reflecting the priority connectivity, the node degree (k_i),node strength (S_i), clustering coefficient (C_i), and closeness (B_i), forming the structural characteristic parameter matrix (I_{ij}):

$$I_{ij} = \begin{bmatrix} k_1 & S_1 & B_1 & C_1 \\ k_2 & S_2 & B_2 & C_2 \\ \ldots & \ldots & \ldots & \ldots \\ k_n & S_n & B_n & C_n \end{bmatrix} \tag{14}$$

Due to the definitions of each parameter and different calculation methods, normalization is required for the subsequent calculation. The normalization formula is as follows:

$$I'_{ij} = \frac{I_{ij}}{\max(I_{ij})} \tag{15}$$

The normalization matrix I'_{ij} is defined as follows:

$$I'_{ij} = \begin{bmatrix} k'_1 & S'_1 & B'_1 & C'_1 \\ k'_2 & S'_2 & B'_2 & C'_2 \\ \ldots & \ldots & \ldots & \ldots \\ k'_n & S'_n & B'_n & C'_n \end{bmatrix} \tag{16}$$

TABLE 4. Judgment matrix.

A	k_i	S_i	B_i	C_i
k_i	1.00	3.00	3.00	3.00
S_i	1/3	1.00	3.00	3.00
B_i	1/3	1/3	1.00	1.00
C_i	1/3	1/3	1.00	1.00

Now, we construct an ideal node, $I'_0 = (k_0, C_0, B_0, S_0)$, and prescribe $I'_0 = \max\{k_i, C_i, B_i, S_i\}$.

The formula for calculating the degree of association r_{0i} between the ideal node I'_0 and the I'_i of node i is as follows:

$$r_{0i} = \sum_{j=1}^{4} \omega_j \xi_{0i}(j) \quad i = 1, 2, \ldots, n \tag{17}$$

where

$$\xi_{0i}(j) = \frac{\min\limits_{\substack{1\leq i\leq n \\ 1\leq j\leq 4}} \Delta_{0i}(j) + \rho \max\limits_{\substack{1\leq i\leq n \\ 1\leq j\leq 4}} \Delta_{0i}(j)}{\Delta_{0i}(j) + \rho \max\limits_{\substack{1\leq i\leq n \\ 1\leq j\leq 4}} \Delta_{0i}(j)}$$

$$i = 1, 2, \ldots, n \tag{18}$$

$$\Delta_{0i}(j) = \left| I'_{ij} - I'_0 \right| \tag{19}$$

In formula (18), the value of the resolution coefficient ρ should affect the final result of the correlation calculation as little as possible. Therefore $\rho = 0.5$, the coefficient ω_j is the weight value coefficient of the corresponding j network indicator, and the weight value is calculated by the AHP.

2) CALCULATION OF COEFFICIENT ω_j BY AHP

1. Construct the judgment matrix A as follows:
2. Let a_{ij} be the judgment matrix elements, and apply the summation method to normalize by column. Let V_{ij} be the normalized result:

$$V_{ij} = a_{ij} / \sum a_{ij} \tag{20}$$

3. Then, normalize the matrix by row, resulting in F_i.

$$F_i = \sum V_{ij} \tag{21}$$

4. Normalize F_i to get the characteristic vector: $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$:

$$\omega_i = F_i / \sum F_i \tag{22}$$

ω is the characteristic vector approximation of matrix A.

5. Find the maximum characteristic value corresponding to the characteristic vector.

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{(A\omega)_i}{\omega_i} \right) \tag{23}$$

6. Apply the consistency test:

$$CI = \frac{\lambda_{\max} - n}{n-1} < 0.1$$

is considered acceptable level of consistency.

After performing the above calculation, the following coefficient matrix is obtained:

$$\omega = (0.47, 0.29, 0.12, 0.12)^T$$
$$CI = \frac{4.146 - 4}{4-1} = 0.048 < 0.1$$

Thus, the result is acceptable.

3) ESTABLISHING THE NODE PRIORITY CONNECTIVITY EVALUATION MODEL

When traffic congestion occurs, drivers will select nodes with higher node degree (k_i),node strength (S_i), clustering coefficient (C_i), and closeness (B_i),as their selection points for traffic evacuation.

Assignment:

$$\omega_k = 0.47, \omega_S = 0.29, \omega_B = 0.12, \omega_C = 0.12$$

Combining formulas (13) to (23), the node priority connectivity evaluation value can be obtained as follows:

$$R = \begin{bmatrix} \xi_{01}^k & \xi_{01}^S & \xi_{01}^B & \xi_{01}^C \\ \xi_{02}^k & \xi_{02}^S & \xi_{02}^B & \xi_{02}^C \\ \cdots & \cdots & \cdots & \cdots \\ \xi_{0n}^k & \xi_{0n}^S & \xi_{0n}^B & \xi_{0n}^C \end{bmatrix} \begin{bmatrix} \omega_k \\ \omega_S \\ \omega_B \\ \omega_C \end{bmatrix} \tag{24}$$

G. CONSTRUCTING AN EVACUATION PATH SELECTION MODEL

In this paper, we propose to use the selection weight Z_{ij} of evacuation node j as the reference quantity to plan the optimal path between the starting node a and the end node b. According to the definition of the distance between complex network nodes, d_{ab} is the number of lines on the shortest path connecting the two nodes a and b. When the value of d_{ab} is fixed, the path (a, b) has at least one connection mode in the traffic network, and the sum of the selection weights of nodes on different connection modes can be compared, and the connection mode with the largest sum selected as the optimal path.

The objective function is as follows:

$$W = \max \sum Z_{ij} \tag{25}$$

Limitation:

$$l_{ij} \in l_{ab}$$

where l_{ab} is the shortest path connecting the two nodes a and b.

In summary, the solution to the congestion evacuation node and path selection model is as follows:

Step 1. Perform the Space L method on the actual traffic network, abstracting the network $G = (N, E)$, consisting of nodes and lines. Calculate the complex characteristic parameters, such as node degree, node strength, clustering coefficient and closeness of the traffic network. Fit the node degree distribution function $p(k)$ to determine the traffic network topology. The distribution law of path of length L between the nodes is analyzed, to obtain the traffic volume q of the road section.

Step 2. Substitute the obtained complex characteristic parameters of each node of the traffic network into the priority selectivity evaluation value model, and calculate the value of each node, matrix R.

Step 3. Investigate and obtain the transit time of each road section, and combine the value R into the selection of weights model to calculate the Z_{ij} of each node j connected to node i. According to the objective function M, the local optimal evacuation node is determined.

Step 4. Obtain several connection methods for the shortest distance between nodes a and b, then calculate the most reasonable evacuation path according to the objective function W.

The selection flow chart is as follows:

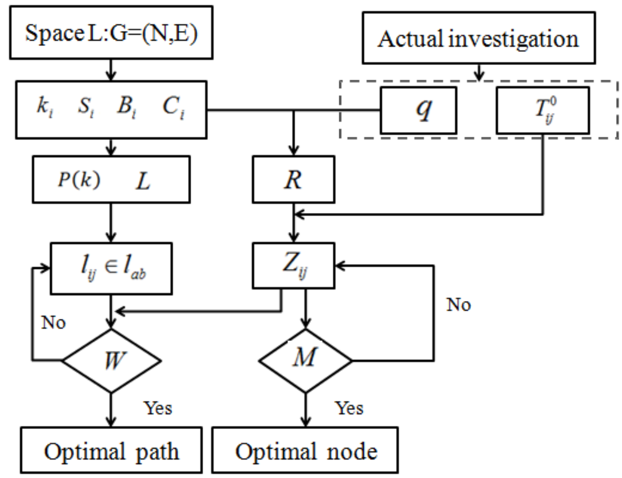

FIGURE 2. Evacuation node and path selection flowchart.

III. CASE STUDY IN CHANGCHUN CITY

An example based on the traffic situation in Chaoyang district (FIGURE 3.) in Changchun City is now used to study the complex characteristics of areal traffic network. In the process of constructing the network model of the urban network, the Space L method is used to abstract the actual road network into a complex network $G = (40, 167)$ [28]. After the network is constructed, the node labels are as shown in FIGURE 4. In order to facilitate the analysis, the road sections with large traffic volumes and the intersections with stable peak hour traffic flow values are selected as the analysis objects. This area is often congested in the morning and

FIGURE 3. Road network diagram.

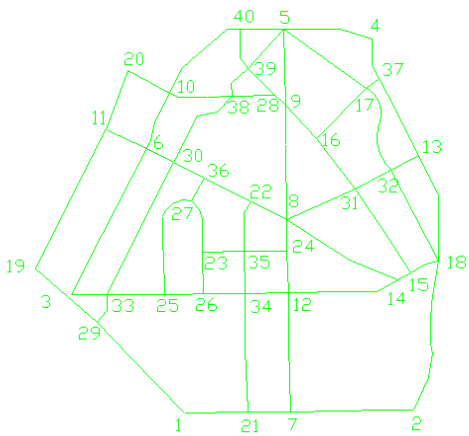

FIGURE 4. Road network label diagram.

evening peak hours and research data have been obtained for it.

A. ANALYSIS OF COMPLEX CHARACTERISTICS OF TRAFFIC NETWORK

According to the definition of the complex network characteristic parameters, the traffic network characteristic parameter values are obtained (TABLE 5).

1) DEGREE DISTRIBUTION ANALYSIS

In this paper, cubic fitting and quartic fitting are performed on the known node degree distribution characteristics, and the distribution law of the node degrees is summarized. The fitting equations are as follows:
Cubic fitting equation:

$$y = x^3 - 17x^2 + 79x - 93 \tag{26}$$

Quartic fitting equation:

$$y = 0.513x^4 - 6.18x^3 + 19.4x^2 + 31.4 \tag{27}$$

TABLE 5. Characteristic parameters value.

Node (i)	Node Degree (k_i)	Node strength (S_i)	Closeness (B_i)	Clustering coefficient (C_i)
1	2	0.61	0.006061	1
2	2	0.63	0.005814	1
3	4	1.09	0.006494	0.5
4	2	1.01	0.006135	1
5	5	2.13	0.007519	0.7
6	4	1.08	0.007042	1
7	3	0.91	0.006623	1
8	5	1.59	0.008333	1
9	4	1.37	0.007752	1
10	4	1.47	0.006849	1
11	3	1.28	0.005650	1
12	4	1.12	0.006897	1
13	3	1	0.005917	1
14	3	0.92	0.007299	1
15	3	0.8	0.006410	1
16	3	0.98	0.006623	1
17	4	1.44	0.006711	1
18	4	1.17	0.006211	0.5
19	2	0.78	0.005291	1
20	2	0.94	0.005556	1
21	3	0.87	0.006667	1
22	3	0.79	0.008130	1
23	3	1.44	0.006410	1
24	3	0.98	0.007246	1
25	3	1.06	0.006536	1
26	3	1.06	0.006452	1
27	3	1.34	0.006711	1
28	3	1.38	0.007299	1
29	3	1.14	0.006452	1
30	4	1.62	0.007813	1
31	4	1.24	0.007042	1
32	4	1.24	0.006623	0.5
33	4	1.62	0.007092	0.5
34	4	1.04	0.006711	1
35	4	1.3	0.007092	1
36	3	0.84	0.007576	1
37	3	2.1	0.005848	1
38	4	2	0.007752	0.5
39	4	2	0.007042	0.5
40	3	1.02	0.006803	1

The fitting equations obtained are not unique but were selected according to actual needs. The fitting results are shown in FIGURE 5.

2) TRAFFIC NETWORK TOPOLOGY DETERMINATION AND VERIFICATION

If there are two edges connected between two nodes in a graph, it is called a double edge. A graph without a circle and a double edge is called a simple graph. Vertex sets and edge sets are limited sets, then the graph is called limited graph.

If a graph G can be drawn on a plane such that there is no intersection between any two edges (ie, there is no other two edges between any intersection except the common

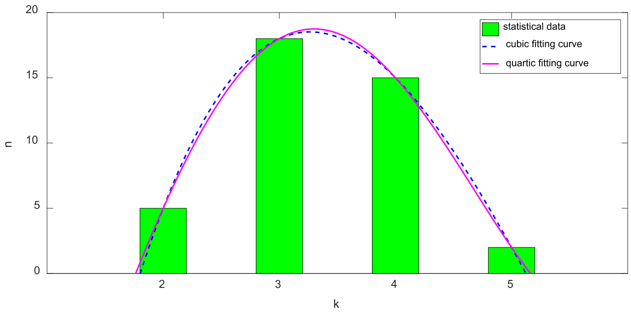

FIGURE 5. Degree distribution characteristic map.

TABLE 6. *d* value and number of node pairs.

d value	1	2	3	4	5	6	7	8
Number of Node pairs	67	119	152	165	135	98	40	3

endpoint), then G can be said to a planar graph. A plan view can be seen as a specific plane embedding of the planar graph. In the process of transforming the traffic road network into a topological graph, the paper combines the urban expressway and the ground road between the two points in order to avoid double edge [29].

The scale of intersections and roads is limited, and then the graph belongs to a simple limited graph. The topology of the formed traffic road network graph does not contain circles and double edges, and there is no intersection between any two roads, then the graph can be considered as a planar graph.

From the above calculation results, we know that the average clustering coefficient of the network is $\overline{C_i} = 0.0608 \ll 1$. The results show that the network does not have a high degree of clustering. The calculations in the paper below show that the network has a small average path length $L = 3.87$. The result indicating that the traffic network has the characteristics of complex network. The curve of the network degree distribution is close to a Poisson distribution.

It can be seen from the fitting curve that the degree distribution is close to the Poisson distribution, but not completely coincides with the Poisson distribution. This paper uses Poisson distribution to express the degree distribution law.
Order:

$$\lambda = \langle k \rangle = 3.35 \tag{28}$$

The degree distribution function of this complex network is:

$$p(k) = \binom{N}{k} p^k (1-p)^{N-k} \approx \frac{\langle k \rangle^k e^{-\langle k \rangle}}{k!} = \frac{3.35^k e^{-3.35}}{k!} \tag{29}$$

3) AVERAGE PATH LENGTH ANALYSIS

By calculating the average path length of the traffic network [1], the number of node-pairs for each value of node distance d (The shortest path length) is as shown in TABLE 6.

Calculated result:

$$L = \frac{2}{N(N-1)} \sum_{i<j} d_{ij} = \frac{2}{40 \times 39} \times 2989 = 3.87$$

This means that any two arbitrary nodes are connected by, on average, about three nodes. Performing a fitting analysis on TABLE 6, produce the following figures.
The cubic fitting equation is as follows:

$$y = x^3 - 23x^2 + 7.06x - 40 \tag{30}$$

It can be seen from FIGURE 7 that the largest number of node pairs are at a distance of 3 or 4, indicating that the traffic network has good connectivity.

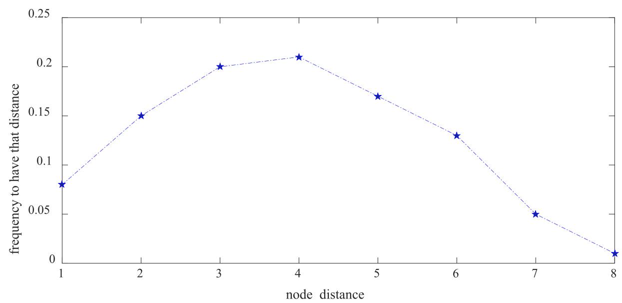

FIGURE 6. Frequency to have that Distances.

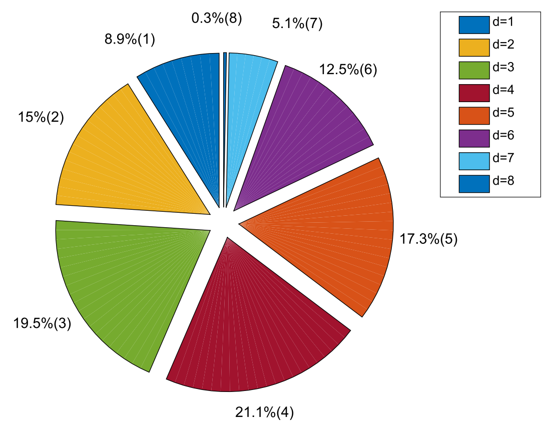

FIGURE 7. Node distance distribution.

In the literature, the analysis of complex network features mainly uses virtual topology networks as the research object, and the results are more ideal in such cases. The traffic network layout of Changchun City has a certain representativeness. The analysis of the complex characteristic parameters of the traffic network reflects the real state of the traffic network. The simulation results of the degree distribution function and the d-value distribution reveal the true topological characteristics of the traffic network. The research results make up for the lack of analysis of real traffic networks in the literature.

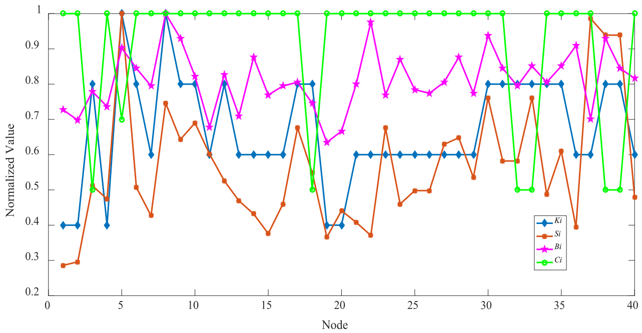

FIGURE 8. Normalized analysis of characteristic parameters values for each node.

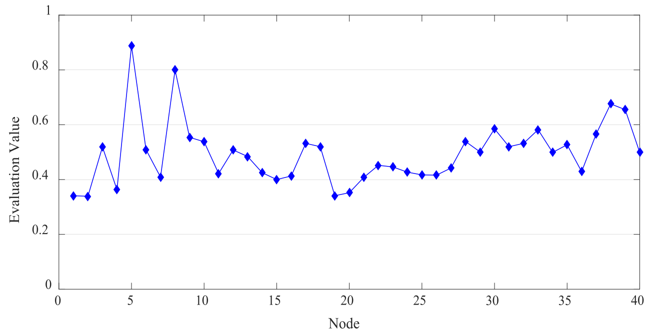

FIGURE 9. Distribution of priority connectivity evaluation values.

B. CALCULATION OF TRAFFIC NETWORK NODE PRIORITY CONNECTIVITY EVALUATION VALUE

Next, the characteristic parameters of the traffic network are normalized and the values are compared. The results are shown in FIGURE 8. The trends in the node degree (k_i), intensity (S_i) and closeness (B_i) are similar, while the clustering coefficient (C_i) does not follow the same pattern. This indicates that the clustering coefficient of the ER model does not have an obvious characteristic distribution law.

According to formula (24), the priority connectivity evaluation value of each node is as shown in TABLE 7.

TABLE 7. Priority connectivity evaluation values for each node.

Node	Value	Node	Value	Node	Value	Node	Value
1	0.341	11	0.422	21	0.408	31	0.520
2	0.339	12	0.508	22	0.452	32	0.532
3	0.519	13	0.484	23	0.446	33	0.582
4	0.363	14	0.425	24	0.427	34	0.499
5	0.888	15	0.400	25	0.417	35	0.527
6	0.509	16	0.413	26	0.416	36	0.429
7	0.409	17	0.532	27	0.442	37	0.566
8	0.800	18	0.520	28	0.539	38	0.676
9	0.554	19	0.341	29	0.501	39	0.655
10	0.538	20	0.352	30	0.585	40	0.499

TABLE 7 shows the tendency of other nodes connected to the fault node to be the traffic evacuation node, given the congestion of a certain in the road network, from a quantitative point of view. The model considers several static complex network characteristic parameters comprehensively, and considers the dynamic parameters that characterize the traffic flow state of the network. The model can comprehensively reflect the state of each node in the traffic network. Nodes with high evaluation values are more likely to become traffic evacuation nodes. Therefore, the evaluation value can be used as a basis for the selection of a traffic evacuation plan.

It can be seen from FIGURE 9 that the priority connectivity evaluation values lie in the range 0.3-0.7, and are concentrated mostly in the vicinity of 0.4-0.6, indicating that the overall operation of the network is relatively stable under the current traffic conditions.

C. CALCULATION OF THE TRANSIT TIME OF THE ROAD SEGMENT

According to formula 10, the transit time T_{ij} of the road segment under known traffic saturation conditions is calculated, and the normalization value T'_{ij} is obtained.

D. EVACUATION NODE AND PATH SELECTION

1) LOCAL EVACUATION NODE SELECTION

To study the practical application of the evacuation model, we must first assume that a node fails. To select the node that fails, reference can be made to the selection of deliberate attack nodes. Since a deliberate attack can easily cause the cascading failure of a network, the deliberate attack node is selected as the failure node, which accurately reflects the effect of the evacuation model in the event of cascading failure of network. If deliberately attacking a network, one would select nodes with higher node degrees and clustering coefficients. Such nodes would have a greater impact on the overall network connectivity [30].
Node selection function:

$$Q_i = k_i + C_i \tag{31}$$

According to TABLE 5, the points with larger Q values are node 8 and node 5. We select these two nodes as the failure nodes.

Substituting the values in TABLES 6 and 7 into formulas(9) to (11), we can calculate the comprehensive weight of each path, and then select the traffic nodes with larger weights as local traffic evacuation nodes.

In the case of emergency evacuation being needed, the path of node 39 is selected as the optimal choice for evacuation from node 5, while the path of node 22 is selected for evacuation from node 8.

2) EVACUATION PATH SELECTION

1. Take the path ending with node 7 and starting from node 5 as an example: $d_{5,7} = 5$.
2. Take the path ending at node 19 and starting from node 15 as an example: $d_{15,19} = 8$.

TABLE 8. Transit time.

Road number	T_{ij}^{0}	q/c	T_{ij}	$T_{ij}^{'}$
1-21	45.84	0.69	47.40	0.282
1-29	94.68	0.7	98.09	0.667
2-7	95.28	0.69	98.52	0.670
2-18	98.74	0.68	101.91	0.696
3-6	136.20	0.73	142.00	1.000
3-19	47.88	0.75	50.15	0.302
3-29	27.60	0.7	28.59	0.139
3-33	29.16	0.73	30.40	0.152
4-5	72.96	0.31	73.06	0.476
4-37	27.26	0.68	28.13	0.135
5-9	71.35	0.64	73.15	0.477
5-17	77.28	0.74	80.76	0.535
5-39	37.20	0.46	37.45	0.206
5-40	34.62	0.72	36.02	0.195
6-10	48.96	0.73	51.05	0.309
6-11	53.40	0.73	55.67	0.344
6-30	49.32	0.73	51.42	0.312
7-12	114.48	0.71	118.84	0.824
7-21	31.56	0.69	32.63	0.169
8-9	91.87	0.71	95.37	0.646
8-14	88.80	0.62	90.77	0.611
8-22	24.96	0.73	26.02	0.119
8-24	26.21	0.71	27.21	0.128
8-31	2.80	0.64	54.13	0.333
9-16	35.70	0.74	37.31	0.205
9-28	39.60	0.54	40.11	0.226
10-20	72.48	0.54	73.41	0.479
10-38	50.22	0.54	50.86	0.308
10-40	67.32	0.72	70.03	0.453
11-19	110.06	0.47	110.86	0.764
11-20	43.46	0.52	43.94	0.255
12-14	88.80	0.73	92.58	0.625
12-24	26.35	0.71	27.36	0.129
12-34	33.12	0.73	34.53	0.184
13-18	101.83	0.68	105.10	0.720
13-32	30.90	0.64	31.68	0.162
13-37	59.14	0.68	61.04	0.385
14-15	9.96	0.73	10.38	0.041
15-18	21.18	0.73	22.08	0.089
15-31	78.60	0.74	82.14	0.545
16-17	56.04	0.54	56.76	0.353
16-31	51.48	0.74	53.80	0.330
17-32	69.48	0.74	72.61	0.473
17-37	10.20	0.54	10.33	0.210
18-32	77.16	0.74	80.63	0.534
21-34	90.60	0.75	94.90	0.642
22-35	51.60	0.75	54.05	0.332
23-26	19.44	0.48	19.60	0.070
22-36	40.92	0.73	42.66	0.246
23-27	54.60	0.48	55.04	0.340

TABLE 8. *(Continued.)* Transit time.

23-35	32.64	0.6	33.27	0.174
24-35	33.48	0.6	34.13	0.181
25-26	30.36	0.73	31.65	0.162
25-27	85.20	0.48	85.88	0.574
25-33	45.42	0.73	47.35	0.281
25-33	45.42	0.73	47.35	0.281
26-34	33.66	0.73	35.09	0.188
27-36	18.24	0.7	18.90	0.065
28-38	33.00	0.54	33.42	0.175
28-39	27.84	0.54	28.20	0.136
29-33	22.68	0.46	22.83	0.095
30-33	116.40	0.46	117.18	0.811
30-36	49.92	0.73	52.05	0.317
30-38	79.20	0.46	79.73	0.527
31-32	24.18	0.64	24.79	0.110
34-35	20.52	0.75	21.49	0.085
38-39	24.78	0.46	24.95	0.111
39-40	29.22	0.54	29.59	0.146

TABLE 9. Evacuation node weights.

Weight of node 5	Weight of node 8
$Z_{5,40}=0.5908$	$Z_{8,9}=0.494$
$Z_{5,39}=0.6967$	$Z_{8,22}=0.5807$
$Z_{5,9}=0.5447$	$Z_{8,24}=0.5605$
$Z_{5,17}=0.5119$	$Z_{8,14}=0.4142$
$Z_{5,4}=0.4113$	$Z_{8,31}=0.5641$

TABLE 10. Evacuation path between nodes 5-and 7 objective function values.

Optional path	Objective function value
5-9-8-24-12-7	$W_{5,7}^{1}=2.7874$
(2)5-17-32-18-2-7	$W_{5,7}^{2}=2.3383$

Comparing the results, we have $W_{5,7}^{1}>W_{5,7}^{2}$,so path (1) is selected as the optimal path.

E. COMPARISON OF METHODS

Dijkstra's algorithm is often used in the literature for the selection of evacuation paths. The Dijkstra algorithm is a typical single-source shortest-path algorithm, used to calculate the shortest path from one node to all other nodes. The main feature is that it expands outwards around the starting node and travels through all nodes until it reaches the end node. When the network has n nodes, the computational complexity is large (n^n), the calculation is huge, and the efficiency is low. The objective function considers only a single factor:

TABLE 11. Evacuation path between nodes 15 and 19: objective function values.

Optional path	Objective function value
(1)15-31-8-22-36-30-6-11-19	$W_{15,19}^{1}=4.3466$
(2)15-31-8-22-36-30-6-3-19	$W_{15,19}^{2}=4.3203$
(3)15-14-8-22-36-30-6-11-19	$W_{15,19}^{3}=4.3479$
(4)15-14-8-22-36-30-6-3-19	$W_{15,19}^{4}=4.3576$
(5)15-14-12-34-26-25-33-3-19	$W_{15,19}^{5}=4.4144$
(6)15-31-8-22-36-30-33-3-19	$W_{15,19}^{6}=4.5121$
(7)15-14-8-22-36-30-33-3-19	$W_{15,19}^{7}=4.5134$

Comparing the results, $W_{15,19}=W_{15,19}^{7}$, so we select path(7)as the optimal path.

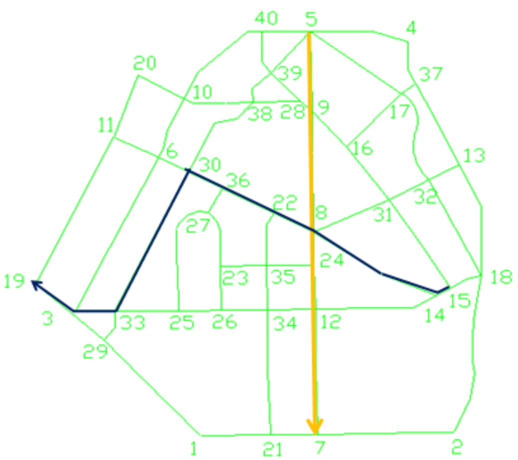

FIGURE 10. Evacuation path selection result.

the shortest time or the shortest path, without comprehensive consideration of the traffic capacity of road intersections, the actual traffic flow of the road sections, and so on.

The evacuation model proposed in this paper has a small computational complexity (n^2) and high efficiency. The objective function takes into account the traffic capacity of the intersections and the saturation of the road traffic, as well as the actual transit times on the roads. The evacuation model considers the topological structure and network characteristic parameters of the traffic network, and provides a practical method for selecting an evacuation path.

IV. CONCLUSION

Based on the demand for congestion evacuation, this paper selects several parameters capturing the complex characteristics of nodes based on the relevant theory of complex networks, namely the node degree, clustering coefficient, node strength and node closeness. The complex characteristics of a traffic network in Chaoyang District of Changchun City are analyzed, the network topology is given, and the complex characteristic parameter values are calculated.

When a traffic network is congested, traffic flow should be evacuated to neighboring nodes. Therefore, the basis for selection of evacuation nodes and paths is considered here. In this paper, the complex parameters of the traffic network nodes are substituted into the grey relational analysis model, and the weights of each parameter are determined by the AHP.A model for the evaluation node priority connectivity values is proposed for the first time. The model refers to the static indicators and the dynamic indicator. This paper comprehensively considers the relevant parameters that determine the traffic conditions of a traffic network. According to the evacuation target, a congestion evacuation node and path selection model is innovatively established.

In this paper, that model is applied, and combined with the definition of complex network node distance. An evacuation path scheme is given for a specified starting – and end node. This can provide a basis for the selection of traffic evacuation nodes and paths from a quantitative perspective.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

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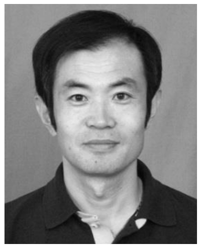

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