Research Article

Complex Traffic Network Analysis Method Based on a Multiscale Aggregation Model

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Identifying the aggregation characteristics of the geospatial network is an important aspect of analyzing highway traffic networks. Based on the complex network theory, this paper studies the block aggregation characteristics of the highway traffic network and proposes an Improved PageRank Spectral Clustering (IPSC) Algorithm to divide the functional blocks of highway traffic networks. Firstly, the theoretical model of a highway traffic network is constructed by adding location attribute weight, geographical distance weight, road grade weight, and dynamic traffic congestion weight. Secondly, the improved PageRank algorithm is used to get the ranking of key nodes of the highway traffic network. The clustering center and the number of clusters are determined by the ranking of key nodes and the shortest path distance. Then the improved spectral clustering algorithm is used to divide the functional blocks of the highway transportation network and identify the special common blocks of the highway transportation network. Finally, the IPSC Algorithm is used to analyze the aggregation mode of complex traffic networks at city and district scales. Crossing the limit of administrative division, the division results of special common blocks of highway transportation networks are obtained. Maintaining the connectivity between blocks can improve the overall efficiency of highway transportation networks.

1. Introduction

The highway transportation network is an important infrastructure to serve the economy, society, and public. In recent years, with the continuous expansion of the urban scale, the rapid growth of the urban population has brought great pressure to urban road traffic. The optimization and intelligent management of road traffic are effective ways to alleviate traffic pressure. Therefore, it is of great significance to analyze and study the road traffic network.

With the rapid development of computers, research on complex networks at home and abroad has become a hot topic in academic circles. Highway transportation network has the characteristics of complex structure, diverse connections, and many road intersections. The mathematical model of highway traffic networks based on complex network theory can analyze the network structure as a whole. The functional block of the highway transportation network is the leading structure showing different characteristics and multiple functions of a complex highway transportation network. In recent years, Du et al. [1] pointed out that the highway transportation network is a complex network with the structural characteristics of a complex network. Qian et al. [2] built a complex road traffic network using the dual method. The time-delay and recovery characteristics of complex road traffic networks are analyzed and compared, and the cascade failure models of complex networks are simulated. Based on complex network and graph theory, Sun
et al. [3] analyzed the network structure of the urban rail transit system and deeply studied the vulnerability of stations. Zeng et al. [4] analyzed the static characteristics of Tianjin urban rail transit represented by the current network and forward network based on complex network theory. In the research, the global efficiency is selected as the evaluation index, and the evolution characteristics of the network are analyzed. Fortunato and Hric [5] proposed that network block detection is one of the most popular topics in modern network science. Yang et al. [6, 7] applied the concept of block detection to the association network of urban traffic state and proposed a new perspective to identify the spatial association mode of traffic state.

Analyzing the highway traffic network based on complex network theory, mining the functional blocks of network structure, and identifying the distribution characteristics of a network from the perspective of geospatial are important aspects of analyzing highway the traffic network. Firstly, a multiscale analysis of a complex traffic network is necessary. Yang [8] proposed that scale is the basic feature of the objective world, and multiscale research is an important means to understand the complex system of the objective world. A highway traffic network has its complexity and systematicness. In order to obtain the scientific and reasonable design strategies and principles of a highway traffic network, the road network should be analyzed from multiple levels and angles. Multiscale research undoubtedly provides a unique perspective for road network analysis. Secondly, there are deficiencies in data types in the existing research on the construction of a highway traffic network model. Tian et al. [9] proposed that urban road traffic is a typical network. Considering the functional characteristics of the urban road network, the weighted network model of the urban road traffic is redefined. However, the influence factors of dynamic weight are not considered when constructing the weighted model of the road traffic network. Zheng et al. [10] studied the dynamic flow information on a scale-free traffic network and found that congestion behavior has an impact on the traffic network. Adding weight influence factors such as dynamic traffic congestion degree to build the theoretical model of a road network can provide more comprehensive theoretical support for traffic decision-making and service personnel. In addition, an appropriate clustering algorithm needs to be selected for road traffic network block division. There are many algorithms for identifying modules in complex networks, such as vertex clustering algorithm [11], density-based algorithm [12, 13], random walk method [14, 15], circuit approximation method [16], and spectral clustering algorithm [17]. Zhu et al. [18] used the \( k \)-means clustering algorithm to analyze the highway traffic network. However, highway transportation network data is typically high-dimensional data. And the ideal cluster of road traffic network data is not necessarily spherical. Therefore, the research results obtained by using the \( k \)-means clustering algorithm to divide the functional blocks of the highway transportation network have certain limitations.

Based on the above background, this paper analyzes the complex traffic network of the multiscale aggregation model. An Improved PageRank Spectral Clustering (IPSC) Algorithm is proposed to divide the functional blocks of the highway traffic network. Firstly, the theoretical analysis model of a highway traffic network with dynamic traffic congestion degree weight influence factor is constructed. Then, an improved PageRank algorithm is used to get the ranking of key nodes in the highway traffic network and scientifically determine the clustering center and the number of clusters. Considering that the spectral clustering algorithm is suitable for processing high-dimensional data and is more adaptable to data distribution, in this paper, an improved spectral clustering algorithm is used to divide the functional blocks of the highway traffic network. The improved PageRank algorithm and the improved spectral clustering form the IPSC Algorithm. The block aggregation characteristics of a highway traffic network across administrative divisions are analyzed using the IPSC Algorithm. Thereby, it can provide decision-making references for traffic planning, design work, and maintenance work.

The rest of the organizational structure of this paper is as follows: Section 2 introduces the multiscale aggregation model. Section 3 introduces the construction of a highway traffic network theoretical model considering dynamic influence factors. Section 4 introduces the functional block division method of highway transportation network (IPSC Algorithm). Section 5 introduces an example of spatial analysis in a multiscale aggregation model. Finally, the conclusion is given in Section 6.

2. Multiscale Aggregation Model

A multiscale analysis is one of the important methods to correctly understand things and phenomena. From coarse to fine or from fine to coarse, analyzing things at different scales (resolution) is called multiscale analysis, also known as multiresolution analysis. Like the human visual mechanism, people’s understanding of things, phenomena, or processes will draw different conclusions due to different scale choices. Some of these conclusions may reflect the essence of things, some may partially reflect, and some may even be wrong understanding. Obviously, only using a single scale can only make a one-sided understanding of things. Different scales are adopted. The details are seen on a small scale, and the whole is seen on a large scale. The combination of multiple scales can have a comprehensive and clear understanding of things. On the other hand, in nature and engineering practice, many phenomena or processes have multiscale characteristics or multiscale effects. At the same time, people often observe and measure phenomena or processes on different scales. Therefore, a multiscale analysis is one of the important methods to correctly understand things and phenomena.

The aggregation model refers to the movement mode formed by a group of moving objects moving together under certain time and space constraints. Aggregation pattern analysis was first proposed in the literature [19, 20]. It is defined as a trajectory model that simulates various mass events, such as celebrations, parades, protests, and traffic jams. In particular, the gathering area is also considered a long-lasting and stable high-density region. Based on the
complex network theory, this paper deeply analyzes the characteristics of network structure and finds that it is generally characterized by agglomeration in actual network structure. Accurate analysis of a road network aggregation pattern has always been the focus of researchers.

This paper analyzes the multiscale aggregation model of a highway traffic network. This refers to analyzing the special common aggregation of the network from different geospatial angles. Crossing the limits of existing administrative common aggregation of the network from different geospatial angles. The theoretical model provides a basic model for subsequent dynamic transportation network analysis. The results of block aggregation characteristics of a highway transportation network across multiple levels are obtained. Then it can provide new scientific decision-making references for traffic planning, design, and maintenance. At the same time, the multiscale aggregation model analysis makes the research method popularized.

3. Construction of Theoretical Model of the Highway Traffic Network Considering Dynamic Influence Factors

A complex network is the complex network topology and dynamic behavior of a complex large-scale network. It consists of a large number of nodes, which are formed by connecting edges with each other. There are two main ways to map highway transport network into a complex network. One is called the Primal Approach, which means that intersections of highway network represent nodes and connecting roads of intersections represent edges. The other is called the Dual Approach, which means that the highway represents the nodes in the transportation network, and the intersections of the highway network represent the connecting edges between the nodes, because the effect of using the original method is very clear and intuitive. And the road network constructed by the original method contains the meaning of realistic geospatial distance. It can achieve everyone’s spatial cognition. Therefore, this paper uses the Primal Approach to construct the topology of highway transport network.

The next step is to consider the practical significance of the highway transportation network. In this paper, the weight factors that affect the network analysis are added to construct the theoretical analysis model of the highway traffic network. The dynamic influence factor is not considered in the theoretical analysis model of the highway transportation network. This results in a gap between the theoretical model and the actual highway transportation network. Based on this situation, this paper builds a theoretical analysis model of a highway traffic network by adding static data including properties of ground objects and facilities, topological distance, highway network grade, and dynamic traffic congestion degree weight influencing factor. This model provides a basic model for subsequent highway transportation network analysis. The theoretical analysis model of the highway transportation network is shown in Figure 1.

Specifically, the structure of the highway transportation network is defined as

\[ RTN = (N, E). \]

where \( N = \{n_i | i = 1, 2, \cdots, N\} \) represents the traffic network node set, \( N = |N| \) which is the number of nodes in the traffic network, and \( E = \{e_{ij} | i \neq j, i, j \in \{1, 2, \cdots, N\}\} \) is a collection of edges. If there is an edge between nodes \( i \) and \( j \), then \( e_{ij} = 1 \); otherwise, \( e_{ij} = 0 \). If each edge is given a corresponding weight, this network is called a weighted network.

3.1. Location. Location attribute is an important factor to measure the importance of road segments. Location characteristics are usually related to the presence of some facilities. Referring to the POI Classification, Layering, and Attribute Structure of Geographic Information Public Service Platform published by Esri China (Beijing) Co., Ltd., the POI of catering, shopping, and other POIs are selected as location prominent attributes. The specific POI categories and codes are shown in Table 1. These POIs are used as 500-meter buffer ranges to view customized location attribute values for covered road network nodes. If the node is within the 500-meter buffer range, it will be a node weighted value of 1. Otherwise, the weighted value is 0. The location attribute weight settings are shown in Table 2.

\[ F = (v_1, v_2, \cdots, v_N). \]

3.2. Distance. In terms of geospatial correlation, highway traffic network has significant distance attenuation characteristics. The spatial correlation generally decreases with the increase of the two distances. Suppose \( W = (w_{ij})_{i,j=1}^{N} \) is the distance weight matrix, where \( w_{ij} \) represents the reciprocal of the shortest path length between node \( i \) and node \( j \).

\[ w_{ij} = \begin{cases} 1/d_{ij}, & i \neq j, 1 \leq i, j \leq N, \\ 0, & i = j \end{cases} \]

where \( d_{ij} \) is the shortest path length between node \( i \) and node \( j \) in the initial transportation network structure, and the unit is "km."

3.3. Road Level. Different grades of highways have different limited speeds and traffic volumes. According to China’s current Technical Standard for Highway Engineering (JTG B01-2014) [21], highways are divided into five grades including expressways, first-class highways, second-class highways, third-class highways, and fourth-class highways according to their use tasks, functions, and traffic volume. According to the different speeds of highways at all levels,
Suppose \( \mathbf{L} = (l_{ij})_{N \times N} \) is a road grade matrix, and element \( l_{ij} \) refers to the weighted value of the road grade in Table 3.

### 3.4. The Degree of Traffic Congestion

Dynamic traffic congestion information is also one of the important factors that affect people’s travel road choice. This paper uses the average travel speed of interval sections (average travel speed of interval sections = number of vehicles measured × length of interval sections/sum of all measured times of vehicles passing through the interval sections) to determine the traffic congestion level during peak travel. The degree of traffic congestion is divided into grade I (severe congestion), grade II (moderate congestion), grade III (mild congestion), and grade IV (unblocked). The lower the average travel speed, the higher the traffic congestion level and the higher the road weight during peak travel period. The weight settings for different traffic congestion levels are shown in Table 4.

Suppose \( \mathbf{T} = (t_{ij})_{N \times N} \) is the traffic congestion level matrix, and element \( t_{ij} \) refers to the weighted value of the traffic congestion level in Table 4.

### 4. Highway Transportation Network Functional Block Partition Method (IPSC Algorithm)

This paper proposes the IPSC Algorithm to divide the functional blocks of a highway traffic network. The IPSC Algorithm is divided into two core parts. One is the improved PageRank algorithm part. This section is used to determine the ordering of critical nodes. The second is the improved spectral clustering algorithm part. This part is used to divide the functional blocks of the road traffic network.

Alex Rodriguez and Alessandro Laio proposed that the core idea of the clustering algorithm lies in the selection of cluster centers [22]. Therefore, the cluster center selection of the clustering algorithm has a very large impact on the clustering results. However, there is currently no standard
method for selecting cluster centers, generally selected randomly or by experience. This has obvious subjectivity, which makes it difficult to guarantee good clustering results. In this paper, the PageRank algorithm is used to determine the ranking of key nodes in the road traffic network by adding the dynamic weight factors of the road traffic network. Then the clustering center is determined by combining the key node sorting and the shortest path distance.

In addition, road traffic network data is typical high-dimensional data. And the ideal cluster of road traffic network data is not necessarily spherical. The k-means algorithm used in previous studies is not effective in identifying nonspherical clusters. Moreover, the k-means algorithm converges to the local optimal solution rather than the global optimal solution. Spectral clustering is an algorithm that evolves from graph theory and is widely used in cluster analysis. It is characterized by the use of dimension reduction techniques and is more suitable for clustering analysis of high-dimensional data such as highway transportation networks. Meanwhile, the spectral clustering algorithm is based on the spectral graph theory. Compared with traditional clustering algorithms, spectral clustering algorithms have the ability to cluster in the arbitrary shape of sample space and converge to the global optimal solution. Therefore, this paper uses a spectral clustering algorithm to partition highway transportation network functional blocks.

At the same time, considering the actual characteristics of highway transportation network itself, this paper adds weight factors such as location, distance, highway grade, and dynamic traffic congestion degree to improve the spectral clustering algorithm, using the improved spectral clustering algorithm to divide the functional blocks of the highway traffic network. This makes the clustering results more in line with the actual road network situation.

### 4.1. The Improved PageRank Algorithm Determines the Ranking of Key Nodes

The PageRank algorithm itself is the only standard used by the Google browser to measure the quality of a website. Google defines the level of websites as 0 to 10, of which 10 means full marks. The higher the PageRank value, the more important (very popular) the website. The Google page is. The advantage of the PageRank algorithm is that it considers the important feedback of connecting other pages. It is suitable for analyzing highway transport network.

Without considering the influence of any weight, the higher the connection degree of the road node, the more important the road node is in the highway traffic network. However, the disadvantage of the PageRank algorithm is that it does not consider the importance of the node itself. Considering the importance of road nodes, this paper adds the weight influence factors of location, road grade, distance, and dynamic traffic congestion degree in the real traffic network to improve the PageRank algorithm. The ranking of key nodes of highway transportation network obtained by using the improved PageRank algorithm is more in line with the actual situation of highway transportation network.

The flow of the improved PageRank algorithm is as follows.

1. PageRank’s Google matrix, represented by $G$, is defined as

$$G = \alpha A^* + \frac{(1-\alpha)}{N} I_{N \times N},$$  

where $A^*$ is the transfer matrix of the adjacency matrix $A$ obtained from the original traffic network, $\alpha$ is the damping factor, which is generally used $\alpha = 0.85$, $N$ represents the number of nodes in the traffic network, and $I_{N \times N}$ is an $N \times N$-order element matrix.

2. A new weighting matrix $K$ is defined by using location attribute matrix $F$, distance weight matrix $W$, road grade matrix $L$, and time-division traffic congestion degree matrix $T$. $k_j$ is the $j$-th column of matrix $K$.

$$K = (k_1, k_2, \ldots, k_j, \ldots, k_N)$$

3. In order to make matrix $K$ irreducible and random, it is necessary to standardize each column vector $k_j$ of matrix $K$ to obtain standard matrix $K_N$.

4. Construct a new matrix $G^*$. Use formula $(1-\alpha)K_N$ instead of formula $(1-\alpha)/N \times I_{N \times N}$, and get

$$G^* = \alpha A^* + (1-\alpha)K_N$$

According to the Perron-Frobenius theorem [23], take the eigenvalue of the eigenvector $\lambda = 1$, and calculate the main eigenvector $X^*_1 = \{g(1), g(2), \ldots, g(N)\}(\lambda = 1)$ of $G^*$ to obtain the level of key nodes; $g(1), g(2), \ldots, g(N)$ represents each component of the principal eigenvector $X^*_1$. The size of the component value represents the importance of the node. The larger the value, the more important the node is, that is, the higher the criticality level.

| Table 3: Distribution of road grade weights. |
|---------------------------------------------|
| Road Expressway | First-class highway | Second-class highway | Third-class highway | Fourth-class highway |
|-----------------|---------------------|----------------------|---------------------|---------------------|
| Weight          | 0.333               | 0.267                | 0.200               | 0.133               | 0.067               |

| Table 4: Distribution of road traffic congestion level weight. |
|---------------------------------------------------------------|
| Traffic congestion degree grade | Pass | Mild | Moderate | Serious |
|-------------------------------|------|------|----------|---------|
| Weight                       | 0.0875 | 0.1875 | 0.3125 | 0.4125 |
4.2. Determine the Cluster Center and the Number of Clusters. Alex Rodriguez and Alessandro Laio pointed out that the cluster center has the following two attributes:

1. Cluster center is an important node surrounded by low-impact neighbors.
2. The initial cluster centers are evenly distributed in the physical network, and the "distance" between the center points is relatively larger.

In this paper, the method of two-dimensional decision graph is used to select the cluster center and the number of clusters. It is easy to understand that the number of cluster centers is the number of clusters. The center point of block detection can be determined by considering $\rho$ and $\delta$, where $\rho$ is the horizontal axis and $\delta$ is the vertical axis:

$$y_i = \rho_i \delta_i, i \in I_5.$$  \hspace{1cm} (7)

$\rho_i$, that is, the $i$-th component of vector $X_i^*$, evaluates the importance of node $i$ and represents the shortest path distance between node $i$ and higher critical nodes. A comprehensive value sequence $\{y_i\}_{i=1}^N$ is calculated, where $y_i = \rho_i \delta_i, i \in I_5$ represents the comprehensive value of node $i$. The larger the reference $y$ value, the more likely it is to be the cluster center. Therefore, it is necessary to arrange $\{y_i\}_{i=1}^N$ in descending order, and then intercept several data points from front to back as the clustering center. Select $m$ nodes distributed at the top right of the decision graph as...
the clustering center, and “m” is the number of clustering clusters.

4.3. Improved Spectral Clustering Algorithm for Functional Block Division of a Highway Traffic Network. At present, the k-means clustering algorithm is mostly used in the research of functional block division of a highway traffic network. However, the k-means clustering algorithm is a prototype-based clustering. Its premise is that the cluster is spherical. Therefore, when using k-means clustering, the original clusters will be spliced to make them appear closer to spherical shape. Therefore, k-means has a better grouping effect on spherical clusters, but not on nonspherical clusters, clusters with different sizes and densities. The spectral clustering algorithm is based on the spectral graph theory. It has the characteristics of being able to cluster in any shape of the sample space and converging to the global optimal solution. It is more adaptable to data distribution. For example, when clustering clusters with three concentric circles in shape, the ideal clustering result should be that the three concentric circles form a class, respectively. The division results of k-means clustering algorithm are shown in Figure 2. Blue, black, and red represent the three categories. The k-means algorithm does not divide each concentric
The division results using the spectral clustering algorithm are shown in Figure 3. The three colors of blue, black, and red represent the three categories. The spectral clustering algorithm divides each concentric circle into one category. The comparison shows that the division result of the spectral clustering algorithm is in line with the expected situation.

The spectral clustering algorithm is not only more adaptable to the data distribution but also uses the dimensionality reduction technology. It is more suitable for processing high-dimensional data such as road traffic networks. Based on the above considerations, this paper uses a spectral clustering algorithm to divide the functional blocks of a highway traffic network. The basic idea of spectral clustering is to decompose the Laplace matrix of sample data. Using the characteristics of Laplace matrix eigenvector data, cluster it based on data mining technology to form a specific clustering scheme. Considering the actual situation
of a highway traffic network, this paper improves the spectral clustering algorithm. On the basis of the similarity matrix, the weight matrix of location, distance, road grade, and traffic congestion degree is added to obtain a new weight matrix in line with the actual road network situation. Then, clustering is carried out to obtain the division results of functional blocks of a highway traffic network.

The flow of the improved spectral clustering algorithm is shown in Algorithm 1.

To sum up, the procedure for dividing the functional blocks of the highway transportation network can be described as the following steps.

Step 1: in the highway traffic network, calculate the adjacency matrix \( A \), location attribute matrix \( F \), distance weight matrix \( W \), road grade matrix \( L \), and time-division traffic congestion degree matrix \( T \)

Step 2: get the ranking of key nodes of a highway traffic network through the improved PageRank algorithm

Step 3: draw a two-dimensional decision diagram according to the ranking of key nodes and the shortest path distance, and select the cluster center. The number of cluster centers is the number of cluster clusters

Step 4: divide the road traffic network into functional blocks based on the improved spectral clustering algorithm

5. Experiment and Analysis

In this paper, a multiscale case study is carried out based on Langfang and Xiong’an New Area demonstration areas. Langfang city and Xiong’an New Area are two administrative regions with different scales. Xiong’an New Area is located in Baoding City, and both Baoding city and Langfang city are located in Hebei Province. The administrative divisions of Langfang city and Xiong’an New Area are shown in Figure 4. Using the IPSC Algorithm, the road network block division results are obtained, and the road traffic network aggregation in Langfang and Xiong’an New Area is obtained. Maintaining the connectivity of the center of each block can improve the operation efficiency of the whole transportation network, so as to provide theoretical reference for traffic management and service system personnel and provide a new model reference for the subsequent maintenance and construction of highway transport network.

5.1. City Level Case Study-Langfang Demonstration Area.

Langfang is located between Beijing and Tianjin and in the hinterland of Bohai Economic Circle. It enjoys the reputation of "Pearl on Beijing-Tianjin Corridor," "Corridor connecting Beijing and Tianjin, Square around Bohai Sea," etc. It is 40 kilometers away from Tiananmen Square, 60 kilometers away from the central area of Tianjin, 70 kilometers away from the capital and Tianjin airports, and 100 kilometers away from Tianjin Xingang. There are 6 main railway lines, 8 expressways, and 25 national and provincial highways criss-crossing in the urban area. Langfang expressway runs through the south-central part of Langfang, Beijing-Shanghai high-speed railway, and Beijing New Airport, which further makes Langfang seamlessly connect with Beijing and Tianjin. By the end of 2017, there were 26 ordinary national and provincial trunk highways with a total length of 775.046 kilometers in Langfang City and 25 highways above grade II, accounting for 100% of the total mileage of maintenance and management highways.

From the perspective of the whole city, the IPSC Algorithm is used to divide the functional blocks of Langfang highway traffic network. Figure 5 shows the distribution of the highway traffic network in Langfang city. Firstly, the Primal Approach is used to construct the topology of Langfang highway traffic network. The theoretical analysis model of Langfang highway traffic network is constructed by adding
the weight influence factors including ground feature and facility attributes, topological distance, highway network grade, and dynamic traffic congestion degree. Then the improved PageRank algorithm is used to determine the ranking of key nodes. A two-dimensional decision graph is constructed by combining the ranking of key nodes and the shortest path distance. According to the two-dimensional decision graph theory in 4.2, the nodes distributed at the top right of the decision graph are selected as the clustering center of Langfang highway transportation network. The red box in Figure 6 shows the selection results of cluster centers in Langfang city obtained from the decision map. It can be seen from Figure 6 that there are three cluster centers of the road traffic network in Langfang City. The number of functional block structures of the road traffic network in Langfang City is three. Using the improved spectral clustering algorithm, the road nodes of Langfang highway traffic network are classified into the corresponding block structure to identify the block division results of the target. Figure 7 shows the final result of using the IPSC Algorithm to divide the functional blocks of the Langfang highway traffic network.

We analyze the practical significance of the experimental results in Langfang city. The blue area in Figure 7 is block 1. The purplish-red area is block 2. The green area is block 3. As the result of block division shows, the road nodes in the block are more closely connected with each other. From the figure, the center positions of the three blocks can be clearly found. From the perspective of geospatial structure, improving the connectivity and convenience of these three block structures can effectively improve the highway traffic situation in Langfang. The route at the center point in the connected graph is the key route. This provides a certain reference basis for relevant departments, showing the trend of highway transportation network connectivity. At the same time, the location of the road traffic network that is mainly maintained and improved can also be determined on the road network connected by the block structure. Improving
the connectivity of central points can improve the connectivity of the whole highway transportation network in Langfang. At the same time, it also maintains the operation efficiency of highway transport network.

5.2. Case Study of District Level-Xiong’an New Area Demonstration Area. Xiong’an New Area is a state-level new area under the jurisdiction of Hebei Province, including Xiong’an County, Rongcheng County, Anxin County, and
some surrounding areas. On April 1, 2017, the Central Committee of the Communist Party of China and the State Council issued a notice deciding to set up a state-level new area, Xiong’an New Area, Hebei Province. There are Beijing-Xiong’an Intercity Railway, Tianjin-Xiong’an Intercity Railway, Gu’an-Baoding Intercity Railway, and Beijing-Shijiazhuang Intercity Railway in Xiong’an New Area and G18 Rongcheng-Wuhai Expressway, G0211 Tianjin-Shijiazhuang Expressway, G45 Daqing-Guangzhou Expressway, S7 Tianjin-Baoding Expressway, and Beijing-Xiong’an Expressway that run through the whole territory. On August 30, 2019, Xiong’an New Area set up Xiong’an District of China (Hebei) Pilot Free Trade Zone. In December 2019, Xiong’an New District was selected as the first batch of pilot areas for the construction of a strong transportation country.

Based on the district perspective, the IPSC Algorithm is used to divide the functional blocks of the highway traffic network in Xiong’an New Area. Figure 8 shows the distribution of the highway traffic network in Xiong’an New Area. First, use the Primal Approach to construct the topology of the highway traffic network in Xiong’an New Area. The theoretical analysis model of the road traffic network in Xiong’an New Area is constructed by adding factors including the attributes of ground objects and facilities, topological distance, road network level, and dynamic traffic congestion degree weight. Then use the improved PageRank algorithm to determine the critical node ordering. A two-dimensional decision graph is constructed by combining key node ranking and shortest path distance. According to the two-dimensional decision graph theory in 4.2, the nodes distributed at the top right of the decision graph are selected as the clustering center of the highway traffic network in Xiong’an New Area. The red box in Figure 9 shows the selection results of cluster centers in Xiong’an New Area obtained from the decision diagram. As can be seen from Figure 9, there are two highway traffic network clustering centers in Xiong’an New Area. The number of functional block structures of the highway transportation network in Xiong’an New Area is two.

The improved spectral clustering algorithm is used to classify the road nodes of the road traffic network in Xiong’an New Area into the corresponding block structure. Thereby, the block division result of the target is identified. Figure 10 shows the results of dividing the functional blocks of the highway traffic network in Xiong’an New Area using the IPSC Algorithm.

We analyze the practical significance of the experimental results in Xiong’an New Area. The purple-red area in Figure 10 is block 1. The green area is block 2. The central points of the two blocks can be clearly seen from the figure. The center points of the two blocks can be clearly seen from the figure. From the perspective of geospatial structure, improving the connectivity and convenience of these two block structures can effectively improve the highway traffic.
Figure 11: Comparison of the division results of functional blocks of the highway traffic network in Langfang City. (a) k-means algorithm. (b) IPSC algorithm.

Figure 12: Comparison of the division results of functional blocks of the highway traffic network in Xiong’an New Area. (a) k-means algorithm. (b) IPSC algorithm.
situation in Xiong’an New Area. At the same time, the connecting route between the central points of the two blocks will be built and maintained, which will reduce the occurrence of dangerous accidents on this road section, ensure highway utilization efficiency, and facilitate people’s living and service facilities. At present, the highway traffic network construction in Xiong’an New Area is not complete. The results of this paper can provide decision-making references for the highway construction in Xiong’an New Area.

5.3. Comparison of k-Means Clustering Algorithm and IPSC Algorithm Example Analysis Results. Figures 11(a) and 12(a) show the results of dividing the functional blocks of the highway traffic network in Langfang City and Xiong’an New Area using the k-means algorithm, respectively. Figures 11(b) and 12(b) show the results of road traffic network function block division in Langfang city and Xiong’an New Area, respectively, using the IPSC Algorithm.

Comparing the results obtained by the two algorithms, it can be seen that the cluster centers in the functional block division results of the highway traffic network obtained by the k-means algorithm are not located in the important positions that connect many roads. This is due to the random selection of clustering centers by the k-means algorithm. In addition, each cluster in the functional block division result of the highway transportation network obtained by using the k-means algorithm is close to a spherical cluster. This is due to the characteristics of the k-means algorithm (that is, it will split the original clusters to make them closer to a spherical shape). The IPSC Algorithm is used to divide the functional blocks of the road traffic network avoids these problems. There are three reasons for this. First, the improved PageRank algorithm in the IPSC Algorithm scientifically determines the cluster center and the number of clusters. Second, the spectral clustering algorithm in the IPSC Algorithm has the advantage of being more adaptable to the data distribution. Third, when the IPSC Algorithm divides the functional blocks of the highway traffic network, the weight factors such as the location attribute, distance, highway grade, and traffic congestion degree of the highway are added. It takes into account the actual situation of the road traffic network. Therefore, the division result of a highway traffic network functional blocks obtained by the IPSC Algorithm is more in line with the actual situation.

6. Conclusion

On the basis of predecessors, this paper analyzes the complex traffic network of the multiscale aggregation model. An Improved PageRank-Spectral Clustering (IPSC) Algorithm is proposed to divide the functional blocks of a highway traffic network. Firstly, the theoretical analysis model of a highway traffic network with dynamic weight influence factors is constructed to provide a basic model for the subsequent research on the functional block division of a highway traffic network. Then, for the problem that the cluster center is difficult to determine, the improved PageRank algorithm is used to determine the ranking of key nodes. Combined with the ranking of key nodes and the shortest path distance, the clustering center and the number of clusters are determined. Then, an improved spectral clustering algorithm is used to divide the functional blocks of a highway traffic network. Finally, combined with the two scales of Langfang city and Xiong’an New Area, the multiscale aggregation model of a complex traffic network is analyzed, and the functional block division results of the highway traffic network in Langfang city and Xiong’an New Area are obtained. It will provide decision-making references for highway construction in both areas.

Data Availability

The traffic network data of Langfang city and Xiong’an New Area used to support the results of this study have not been available because the original road network data is the traffic situation of the real county location in China. It can reflect the real data of China’s geographical location. Therefore, it cannot be made public. However, the results of the later results can be referenced and applied.

Conflicts of Interest

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

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