Research Article

Research on Algorithm Complexity of Spatial Structure of Urban Economic Logistics Specialty

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1.Introduction

Regional spatial structure refers to the spatial location relationship of socioeconomic objects, as well as the interaction in space and the formation of a degree of spatial agglomeration and agglomeration pattern [1], which can be traced back to the classical location theory and growth pole theory at the earliest, and the earliest theoretical foundation was laid by Lu Daodao and Lu Yuqi in China, which put forward the classical “point-axis” system, “I” structure [2], and dual-core structure theory [3]; the theory of spatial regional structure was gradually applied to industrial economy [4], tourism and transportation [5], transportation geography [6], regional and urban logistics planning [7], and other fields. As China enters a period of rapid development, air logistics play an increasingly important role in intercity trade activities and economic cooperation, and the analysis of the spatial structure of air networks has subsequently become a research hotspot in recent years.

In the context of the dual transformation and development of economic globalization and regional integration, the mobility of production factors between cities continues to increase. Since the 1990s when Castells proposed the concept of flow space with circulation factors as a regional research paradigm [8], this related research system has been continuously improved [9], and regional flow space research has become one of the hot issues of academic research. It mainly involves the circulation of physical goods and the transportation of virtual resources [10], which expands the research perspective of regional spatial linkage network. In the exploration of regional economy, transportation flow can construct the geographical linkage between regions and promote the development of regional integration [11]; information flow and capital flow can break through spatial restrictions [12], as the transport of production and living factors pillar industry, in the process of rapid urbanization, the logistics industry structure and industrial development level have undergone a great transformation [13]; logistics
greatly promotes the effective flow of factors, optimizes regional resource allocation and is one of the important sources of urban economic development [5], which has also caused the relevant government departments to be sufficiently important to the development of regional logistics, of which promulgated by the State Council emphasises the need to promote the restructuring of the logistics industry, transform the original mode of development, strengthen the construction of logistics networks, and coordinate the development of regional logistics, so as to improve regional competitiveness and promote the construction of ecological civilization.

As a highly developed and complex system, the network connection of urban areas covers a wide range of economic, social, cultural, and political dimensions [14]. With the rise of the new economy, exchanges between regions are becoming increasingly close, and regional development is gradually moving from individual development to an interconnected whole, with spatial connections generated by each other [14], and the degree of interdependence between regions is increasing. Research on regional spatial structure has received the attention of many scholars [14], and some scholars have revealed the laws of economic evolution through numerical measurement of spatial linkages and analysis of network structures, while others have analysed the spatial structure of regional networks from the perspective of industrial factor linkages [15]; meanwhile, for the exploration of the spatial structure of regional logistics, there are in-depth discussions on the spatial characteristics of intercity road freight transport in China based on road freight linkage data [16]. The spatial network characteristics of regional logistics networks have been explored based on road freight linkage data [16], and the spatial pattern evolution of logistics clusters has also been explored using multisource data to identify the development level, type, and development mode of logistics clusters [17], but more regional logistics networks have been constructed using gravity models [9]. In particular, research on regional logistics spatial linkages and the driving mechanism for the formation of regional logistics spatial linkage patterns in the Yangtze River Economic Belt has not been fully developed.

Research on regional logistics in the Yangtze River basin is mainly in the Yangtze River Delta, but there is less research on regional logistics spatial linkages in the Yangtze River Economic Belt, especially the influence mechanism behind the evolution of regional logistics spatial linkages. This study explores the characteristics of regional logistics spatial linkage networks in the Yangtze River Economic Belt based on the gravity model, constructs an axial-spoke network structure from the perspective of city clusters, builds an empirical research framework on spatial linkages, and finally measures the driving mechanism of the formation of logistics spatial linkage patterns through a spatial econometric model, with a view to providing theoretical support for the high-quality development of regional logistics in the Yangtze River Economic Belt.

2. Methodology

In this section, we will introduce the data used in this work and show more details about our models.

2.1. Data Sources and Study Area. The Yangtze River Economic Belt, which covers nine provinces and two cities around the Yangtze River basin, including 109 cities in the Yangtze River Delta city cluster, the middle reaches of the Yangtze River city cluster (Jiangxi, Hubei, and Hunan), and the Pan-Chengdu-Chongqing city cluster, is the area of analysis in this study. In 2016, the Yangtze River Economic Belt supported 43.1% of the country’s total economic output with a land area of only about 21.4% of the country, forming the largest industrial economic belt in the country.

The data required for this study on the regional logistics comprehensive capacity evaluation system of the Yangtze River Economic Belt were obtained from the 2007–2017 China City Statistical Yearbook, and, for the few missing data, they were estimated using data analogy with neighboring regions in the region and combined with the interpolation method, and the time cost distance between cities used in the gravity model was obtained in bulk through the Baidu API function.

2.2. Research Model. Comprehensive regional logistics capacity is an indicator to measure the level of development of regional logistics industry, representing the strength of regional logistics competitiveness. The higher the regional logistics integrated capacity, the stronger the level of logistics industry development and the closer the region’s logistics spatial connection to other cities. According to the method of relevant scholars, this study uses the entropy weight-TOPSIS method to evaluate the regional logistics integrated capacity of the Yangtze River Economic Zone.

In order to avoid subjective influence on the weight, this study adopts the entropy weight method to ranking evaluation objects according to their relative proximity to an idealised target and evaluates the relative merits of a finite number of objects. The main calculation steps of the entropy-weight-TOPSIS method are as follows:

(1) For m evaluation indicators and n evaluation samples, for the jth evaluation indicator and the ith evaluation sample, construct the evaluation matrix \([x_{ij}]_{n \times m}\) and dimensionlessly represent it.

(2) Calculate the information entropy value of each indicator:

\[
e_j = \frac{1}{\ln n} \sum_{i=1}^{n} x_{ij} \ln x_{ij},
\]

(3) Then determine the weights of each indicator:

\[
w_j = \frac{(1 - e_j)}{\sum_{j=1}^{n} (1 - e_j)}.
\]

(4) Multiply the weights with the normalization matrix to obtain the evaluation matrix:
\[ M = \left[ m_{ij} \right]_{n \times n}, \quad m_{ij} = w_{j}x_{ij}. \]  

(3)

(5) Determine the optimal solution \( S'_{i} \) and the inferior solution \( S_{ij} \):

\[ S'_{i} = \max \left( m_{ij}, m_{2j}, \ldots, m_{nj} \right), \]
\[ S_{ij} = \min \left( m_{ij}, m_{2j}, \ldots, m_{nj} \right). \]  

(4)

(6) Calculate the Euclidean distance for each item to be evaluated to obtain the final combined evaluation:

\[ C_{i} = D_{i}^{+}/D_{i}^{-} = D_{i}^{-}C_{i} = D_{i}^{-}/D_{i}^{+} + D_{i}^{-}. \]  

(5)

In the above formula, \( C_{i} \) is the relative closeness of item \( i \) to the optimal solution; a higher value indicates a better evaluation sample.

In this study, to explore the logistics linkage network among the cities in the Yangtze River Economic Belt in detail, a gravitational model is constructed to analyse the interregional role, abstracting the logistics network as network nodes, abstracting the gravitational force reflecting the logistics linkage among the network nodes as network connecting lines, and using the gravitational strength of the logistics linkage to reflect the linkage value among the network nodes. The distance between cities is calculated by considering the traffic complexity of the Yangtze River Economic Zone, and according to the practice of related scholars [18], the distance between cities is calculated by considering the traffic complexity of the Yangtze River Economic Zone, and according to the practice of related scholars [18], the distance between cities in the Yangtze River Economic Zone is calculated by using the time cost distance, and the gravitational force model is modified, and the calculation formula is as follows:

\[ R_{ij} = \frac{KM_{i}M_{j}}{T_{ij}}. \]  

(6)

In the above equation, \( R_{ij} \) represents the strength of logistics gravity between logistics node study units \( i \) and \( j \); \( K \) is the gravitational constant of logistics gravity between logistics node study units, usually taking a value of 1; \( M_{i} \) and \( M_{j} \) represent the logistics “quality” of study unit \( i \) and study unit \( j \); \( T_{ij} \) is the time cost distance between city \( i \) and city \( j \), and \( \theta \) is often taken as 2.

The maximum gravitational line shows the local regional logistics influence of the Yangtze River Economic Zone, while the potential model shows the global influence and identifies cities with relatively high central position. For any county \( i \) that is spatially connected to other cities, there is a maximum gravitational value \( G_{ij}^{\text{max}} \) with a city, and the network line where this maximum gravitational value is located is called the maximum gravitational line, while the potential energy model shows the sum of the spatial connection values between a city and other cities [19]. The maximum gravitational value \( G_{ij}^{\text{max}} \) and the potential energy \( P_{i} \) are, respectively, formulated as follows:

\[ G_{ij}^{\text{max}} = \max \left( G_{ij1}, G_{ij2}, G_{ij3}, \ldots, G_{ijk} \right), \]
\[ P_{i} = \sum_{j=1}^{k} G_{ij}. \]  

(7)

### 3. Quantitative Indicators

Based on social network analysis, five quantitative indicators were selected to reflect the spatial structure of the air logistics network.

#### 3.1. Core Degrees

A continuous core-edge model is developed to calculate the core degree of each node for a directed multivalued network of air logistics in Yunnan Province:

\[ \rho = \sum_{ij} a_{ij} \delta_{ij}, \]  

\[ \delta_{ij} = c_{ij} c_{ji}. \]  

(8)

The idea behind the core-edge model is to find the core, half-edge, and edge points in the network by comparing the star-shaped network, as shown in Figure 1. The matrix corresponding to the ideal network can be called the pattern matrix, denoted as \( \Delta \), and it is composed of \( \delta_{ij} \). In (7), \( \rho \) is a measure, and \( a_{ij} \) denotes the volume of freight between points \( i \) and \( j \). Since the directed network requires the data to be symmetrized when performing core-edge model analysis, in the thesis, \( a_{ij} = \max \left( \bar{a}_{ij}, \bar{a}_{ji} \right) \), and \( \bar{a}_{ij} \) denotes the volume of air freight from point \( i \) to point \( j \) and \( \bar{a}_{ji} \) denotes the volume of air freight from point \( j \) to point \( i \). The mode matrix \( \Delta \) is defined by (8), and \( c \) is the core degree of each point, which is a nonnegative vector.

If the individual values have a fixed distribution, then the measure \( \rho \) reaches its maximum value when and only when the adjacency matrix \( A \) of \( a_{ij} \) and the matrix \( \Delta \) of \( \delta_{ij} \) are equal. Thus, this structure is a core-edge structure as far as \( \rho \) reaches its maximum value. The purpose model is to test each value of \( c \) such that the correlation coefficient between the actual data matrix and the pattern matrix is maximised, resulting in a unique core degree value \( c \).

#### 3.2. Side Correlation

According to the definition of a Lambda set, any pair of points inside a subgraph Ns has an edge correlation greater than that of any pair consisting of a point from Ns and a point outside Ns. Cohesive subgroup analysis uses edge correlations to partition Lambda sets [20].

#### 3.3. Limiting System

The limiting system refers to the ability to use the structural holes in the network, that is, the ability to control the transfer of information, in a directional way. As an example, the limiting system \( S_{ij} \) for point \( i \) subject to point \( j \) is calculated as follows:

\[ S_{ij} = \left( p_{ij} + \sum_{q} p_{iq} p_{qj} \right)^{2}, \]  

(9)

where \( p_{ij} \) is the proportion of air freight from point \( i \) directly to point \( j \) in the overall network; \( p_{iq} p_{qj} \) is the proportion of air freight from point \( i \) through point \( q \) to point \( j \) in the overall network, as shown in Figure 2.
3.4. Grade Level. Also known as the Coleman-Taylor disorder index, the rank degree $H_i$ for point $i$ is calculated as follows:

$$H_i = \frac{\sum_j (S_{ij}/S/n)\ln(S_{ij}/S/n)}{n\ln(n)}.$$ \hspace{1cm} (10)

3.5. Redundancy. Redundancy is a quantitative metric for describing redundant connections between nodes in a network. A nonredundant connection indicates that there are fewer connections between nodes in the network, in terms of edges, that is, the minimum number of edges that can be used to present an effective connection between the nodes in the network, and connections of redundant lines are referred to as redundant connections. The degree of redundancy $R_i$ of a point $i$ is equal to the average degree in the network of the individual network members in which the point is located [7].

$$R_i = \frac{2t}{n}.$$ \hspace{1cm} (11)

4. Time Complexity Analysis Theory

The algorithm’s time complexity can be abstracted from the actual computer running the algorithm and the quantified result is not dependent on the computer. Mathematical theory is used to establish the time complexity function, which is defined as follows: let $I$ be the input data of an algorithm at a certain run, with a scale of $k$. The time complexity $T$ of an algorithm is a function of $k$ and $I$, noted as $T(k, I)$. The algorithm execution steps are split into the basic operations of addition, subtraction, multiplication, division, and assignment, each of which is executed $e_j$, with $e_j$ also as a function of $k$ and $I$, denoted as $e_j(k, I)$, and the time to perform each of these basic operations is $t_i$; then we have

$$T(k, I) = \sum_{i=1}^{l} t_i e_i(k, I),$$ \hspace{1cm} (12)

where $T(k, I)$ is the algorithm’s time complexity function; $t_i$ is the abstraction time of the basic operation, not the actual running time; and $l$ is the number of basic operations.

Obviously, when analysing the time complexity of an algorithm, it is not necessary to count all the basic operations but to consider only the basic operations that are representative [21]. Nowadays, the difference in the speed of computer execution of addition, subtraction, multiplication, and division operations is very small, so the computation times of the four operations are considered to be the same, and the time complexity function can be simplified as

$$T(k, I) = t \sum_{i=1}^{k} e_i(k, I),$$ \hspace{1cm} (13)

where $t$ is the time taken by the algorithm to perform one quadratic operation, generally taken as a unit of time; and $\sum_{i=1}^{k} e_i(k, I)$ is the total number of operations of all quadratic operations, that is, the amount of computation of the algorithm. The amount of computation in an algorithm can be measured by the number of floating-point operations, called the flop count. A single flop is a floating-point operation [22].

In general, the algorithm’s time complexity can be distinguished in terms of optimal, average, and worst case. The optimal time complexity of an algorithm represents the performance of the best case of the algorithm, which is not representative of typical results due to its small probability of occurrence. The average complexity of an algorithm, on the other hand, usually reflects typical results but is more...
cumbersome to analyse. The worst time complexity of an algorithm is most commonly used to represent the worst-case performance of an algorithm, and although this case also has a small probability of occurrence, it gives an upper bound on the complexity of the algorithm and is a guarantee of its performance [23].

Let $T(k)$ and $f(k)$ be functions with $k$ as a variable. A function $f(k)$ is said to be an upper bound on a function $T(k)$ if there exist positive constants $c$ and $k_0$ such that $T(k) \leq cf(k)$ when $k \geq k_0$, denoted as

$$T(k) = O[f(k)],$$  \hspace{2cm} (14)

where $O[f(k)]$ is the asymptotic time complexity of the algorithm, which can be abbreviated as time complexity, and $O$ is the magnitude.

In summary, the time complexity of an algorithm is usually expressed in two ways: one is to obtain the full form of the time complexity function $g(k)$ by definition; the other is to express the higher order term $O[f(k)]$ of $g(k)$; the asymptotic time complexity of the algorithm reflects the growth rate of the complexity of the algorithm. The type of function of $g(k)$ determines the type of algorithm; if $g(k)$ is a polynomial function, then the algorithm is a polynomial algorithm, and if $g(k)$ is an exponential function, then the algorithm is an exponential algorithm [24].

5. Spatial Linkage Pattern of Regional Logistics

5.1. Analysis of the Comprehensive Regional Logistics Capacity. After establishing the evaluation index system, the entropy weighting method was applied to determine the index weights, in order to avoid the influence of individual years, as shown in Table 1 that the data for three years, 2006, 2011, and 2016, and the mean values were calculated, and the mean data were $X_1(0.0947), X_2(0.1222), X_3(0.0992), X_4(0.1027), X_5(0.1627), X_6(0.0686), X_7(0.1405), X_8(0.0675), \text{and} X_9(0.1421)$. The highest weighting can be seen from the weighting of the number of logistics employees ($X_5$), with a mean value of 0.162 7, which indicates that the number of regional logistics employees is the main component of the comprehensive regional logistics capacity ($X_4$), the number of logistics employees ($X_5$), Internet access users ($X_7$), and postal services ($X_9$), which have higher weights and play a greater role in evaluating the level of regional logistics development in the Yangtze River Economic Belt [25].

5.2. Spatial and Temporal Differences. In order to better illustrate the characteristics of spatial and temporal differentiation, this study selected data from three time nodes, 2006, 2011, and 2016, and divided the calculated comprehensive logistics capacity evaluation values into five types, high, higher, medium, lower, and low values, according to the five types of natural breakpoints of ArcGIS 10.1, and Figure 3 is drawn.

According to Figure 3, the overall regional logistics level of all cities in the Yangtze River Economic Belt has increased to a certain extent, with the Chengdu-Chongqing city cluster being the main area with strong comprehensive logistics capacity, that is, showing the spatial distribution characteristics of clustering based on city clusters. In 2006, the spatial characteristics of the Yangtze River Economic Zone were "one core, many points," with only Shanghai reaching a high-value level, Chongqing and Wuhan being the only regions with a high-value level, Nanjing, Wuxi, Xuzhou, Suzhou, Hangzhou, Ningbo, and Nanchang being the seven regions with a medium value level, and 99 regions with a medium value level or less. The number of regions below the median level was 99, accounting for 90.83%; by 2011, due to regional economic development and improved transportation conditions, regional logistics had achieved greater development, and the spatial pattern of regional logistics had also changed significantly, with Chongqing leading to become a high-value region, showing a “double core” of Shanghai and Chongqing. Nanjing, Wuxi, Suzhou, Hangzhou, Ningbo, Hefei, Wuhan, and Chengdu are located in the higher value regions, while Xuzhou, Changzhou, Nantong, Yangzhou, Wenzhou, Shaoxing, Taizhou, Nanchang, Xiaogan, Changsha, Zunyi, and Kunming are the 12 regions that have reached the medium value level, and the number of regions below the medium level is 87, accounting for 79.82%. At the end of 2016, the number of high-value regions also changed significantly, with a “multicore” development trend emerging as well as a more block-like distribution. At the end of 2016, the number of high-value regions has also changed significantly, with a “multicore” development trend emerging and a blocky distribution, with Shanghai, Suzhou, Hangzhou, Chongqing, and Chengdu all located in high-value regions, while the number of higher-value region types was relatively stable and the specific regions have been slightly adjusted to a total of 12 regions: Nanjing, Wuxi, Xuzhou, Changzhou, Nantong, Ningbo, Wenzhou, Hefei, Luan, Wuhan, Changsha, and Kunming. The number of medium-value regions has reached 20 regions, including Jiaxing, Shaoxing, Jinhua, Taizhou, Wuhu, Fuyang, Nanchang, Ganzhou, Yichang, Xiangyang, Xiantan, Meishan, Guiyang, and Zunyi. The number of regions below the median level was 72, accounting for 66.06%, while the spatial compression of low-level regions was more obvious than that in 2006. This shows that the regional logistics level of the Yangtze River Economic Belt has been improved to a certain extent during the study period, further realising the optimization of the regional factor transport function.

5.3. Analysis of Regional Logistics Spatial Linkage Characteristics. The spatial linkage potential energy of logistics measures the total spatial linkage strength of node cities and other cities in the Yangtze River Economic Belt, and the trend surface analysis can better analyse the spatial evolution trend of spatial linkage potential energy. Figure 4 indicates that the development scale of logistics linkage potential is relatively large in the upstream and downstream regions of the Yangtze River as well as in the cities along the river. Based on the analysis from the perspective of time evolution, in 2006, the ratio of the total potential energy of Jiangsu, Zhejiang, and Shanghai to the total Yangtze River Economic Zone was 73.21%, which obviously shows that the
Table 1: Integrated urban logistics capacity evaluation indicators.

<table>
<thead>
<tr>
<th>Primary index</th>
<th>Secondary index</th>
<th>Variable representation</th>
<th>Entropy weight in 2006</th>
<th>Entropy weight in 2011</th>
<th>Entropy weight in 2016</th>
<th>Mean value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Logistics demand scale</strong></td>
<td>Regional GDP</td>
<td>X1 0.0914</td>
<td>0.0948</td>
<td>0.0977</td>
<td>0.0947</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gross industrial output value</td>
<td>X2 0.151</td>
<td>0.1149</td>
<td>0.1006</td>
<td>0.1222</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total retail sales of consumer goods in the whole society</td>
<td>X3 0.0919</td>
<td>0.1029</td>
<td>0.1027</td>
<td>0.0992</td>
<td></td>
</tr>
<tr>
<td><strong>Basic level of logistics</strong></td>
<td>Urban road area</td>
<td>X4 0.1141</td>
<td>0.0932</td>
<td>0.1007</td>
<td>0.1027</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of logistics employees</td>
<td>X5 0.1264</td>
<td>0.1685</td>
<td>0.1931</td>
<td>0.1627</td>
<td></td>
</tr>
<tr>
<td><strong>Logistics information degree</strong></td>
<td>Number of mobile phone users</td>
<td>X6 0.0772</td>
<td>0.0638</td>
<td>0.0648</td>
<td>0.0686</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Internet access user</td>
<td>X7 0.1856</td>
<td>0.1559</td>
<td>0.0798</td>
<td>0.1405</td>
<td></td>
</tr>
<tr>
<td><strong>Logistics scale level</strong></td>
<td>Total freight volume</td>
<td>X8 0.066</td>
<td>0.0639</td>
<td>0.0726</td>
<td>0.0675</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total postal business</td>
<td>X9 0.0963</td>
<td>0.142</td>
<td>0.1879</td>
<td>0.1421</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3: Spatial differentiation of regional logistics integrated capacity in the Yangtze River Economic Belt in 2006, 2011, and 2016.

Figure 4: Regional logistics spatial linkage potential trend surface changes.
development level of logistics in the Yangtze River Delta region is higher and more attractive to other cities; in 2011, the ratio of the total potential energy of Jiangsu, Zhejiang, and Shanghai to the total Yangtze River Economic Zone was 68.74%, which indicates that Jiangsu, Zhejiang, and Shanghai still represent the core region, but, with the development of the surrounding cities, the overall influence of regional logistics has not increased as much as that of the middle and upper reaches of the Yangtze River region; in 2016, the ratio of the total value of potential energy of Jiangsu, Zhejiang, and Shanghai to the total Yangtze River Economic Belt was 70.20%, a slight increase in the ratio, while the proportion of the Chengdu-Chongqing city cluster increased from 5.67% in 2006 to 9.16% in 2016 [26].

In order to investigate the regional influence of cities with logistics advantages, this study constructs a gravitational matrix between cities in the Yangtze River Economic Zone, extracts the gravitational value of each city and its corresponding maximum gravitational city, and obtains a map of the maximum gravitational line linkage of cities.

As can be seen from Figure 5, in 2006, most cities in the entire Yangtze River Economic Belt were linked by a few core cities, mainly Shanghai (24), Nanjing (9), Nanchang (8), Wuhan (14), Changsha (8), Chongqing (11), Chengdu (9), and Kunming (8), accounting for 83.49% of the total number of linkages, which have a good regional economic foundation and location advantages, and the second and third industries dominate. These cities have a good regional economic foundation and location advantages, with the second and third industries occupying a dominant position, as well as the rapid take-off of e-commerce driving the rapid development of regional logistics, forming an obvious "multicore" structure and a strong influence on the logistics of neighbouring cities; in 2011, the pattern of the largest gravitational line linkages did not change much, with the following cities as cores: Shanghai (9), Nanjing (6), Hefei (9), Wuhan (11), Nanchang (6), Changsha (10), Chongqing (17), Chengdu (7), and Kunming (7), accounting for 75.23% of the total. In 2016, the following cities were mainly at the core: Suzhou (8), Nanjing (9), Hangzhou (10), Xuzhou (5), Hefei (4), Wuhan (10), Nanchang (4), Changsha (11), Chongqing (9), Chengdu (15), and Kunming (7), accounting for 84.40% of the total. Overall, the pattern of maximum gravitational lines in the Yangtze River Economic Belt was generally stable during the study period, with most cities in the middle and upper reaches of the Yangtze River having relatively low levels of logistics development and economically developed cities having greater logistics influence, making the structure of regional logistics spatial linkages relatively simple, with little change in the pattern of maximum gravitational line linkages, while most of the cities in the Yangtze River Delta city cluster developed more prominently and the influence of core cities weakened. The regional logistics construction and urban economic development of cities such as Suzhou, Nanjing, Hefei, and Hangzhou, in particular, have not only stimulated the economic and logistics development of the surrounding cities but also made the original core city of Shanghai weaker in terms of its radiating effect on the logistics of geographically distant cities, and eventually the linkage pattern of the Yangtze River Delta developed from the initial "pole-type" spatial pattern with Shanghai as the main core to the later "pole-type" spatial pattern. The spatial pattern of the Yangtze River Delta eventually developed from the initial "pole-type" spatial pattern with Shanghai as the main core to the later multicore pattern.

5.4. Network Structure Analysis of Regional Logistics Spatial Linkages. In order to reveal more deeply the spatial con- nection characteristics of regional logistics, the spatial dis- tribution of logistics spatial connection potential energy and the spatial pattern of maximum gravitational lines can reflect the central position and radiation intensity of cities, and the network structure analysis can further explore the spatial connection characteristics. In order to highlight the main features of the spatial network, the network segments less than 1 (weak link), 1–10 (weak link), 10–50 (average link), 50–100 (strong link), and more than 100 (strong link) are set as transparent. The results are shown in Figure 6.

As can be seen from Figure 6, in 2006, the network structure of spatial logistics links among cities in the Yangtze River Economic Zone was relatively simple, with 32 groups of spatial links of average strength or above. Hangzhou, Hangzhou-Shaoxing, Suzhou-Wuxi, Wuhan-Xiaogan, and 102 groups of spatial links of average strength or higher, and the Yangtze River Delta city cluster has gradually expanded from the previous single-level network structure to a multi- level. The Yangtze River Economic Zone cities have gradually expanded from a single-level network structure to a multilevel network structure that includes most of the surrounding cities, with a dense distribution of network links above average strength and a scattered network with Chengdu and Chongqing as the core in the upper Yangtze River region; by 2016, the spatial logistics links between cities in the Yangtze River Economic Zone were even closer, with 34 groups of strong links and 237 groups of spatial links above average strength, with obvious changes in the network structure. With the continuous development of urban logistics level, the logistics spatial linkage network in the Yangtze River Delta region has become more complex, covering almost all cities, and a scattered network structure with Changsha and Wuhan as the dual cores has been formed in the middle Yangtze River region, while the logistics spatial linkage between cities in the upstream region has been strengthened and a network ring structure has gradually formed. On the whole, the spatial network of logistics links in the Yangtze River Economic Belt is unevenly distributed and has significant hierarchical characteristics, showing a trend of gradually decreasing complexity in the spatial linkage network structure of the downstream, upstream, and midstream cities, while the regional network structure of the Yangtze River Delta city cluster is already more complex, and, with the trend of continuous extension and expansion of regional logistics as a whole, the links with the midstream city cluster and the Chengdu-Chongqing city cluster have been strengthened, gradually forming internal and external expansion. A strong development network with internal and external expansion is gradually formed.
6. Time Complexity Comparison

By performing a nonlinear time analysis on the above structure, a curve of the number of plastic degrees of freedom generated by each nonlinear step of the structure is obtained, as shown in Figure 7. The time complexity of each step of the proposed force method can be obtained by using the time complexity function of the method in this paper, combined with the information from the model data of this example. The time complexities of the two methods are compared and the results are presented in Table 2, where the number of plastic degrees of freedom generated is represented by a maximum value of \( d_1 = 816 \), a higher probability of occurrence of \( d_2 = 200 \), and a mean value of \( d_3 = 53 \).

As can be seen from Table 2 and Figure 7, the time complexity of the proposed force method reaches a maximum value about \( 1.95 \times 10^8 \) when the resulting plastic degree of freedom is the maximum value of \( d_1 \), which is much higher than the rest of the calculation steps, and the average time complexity of the whole time course is about \( 1.46 \times 10^7 \). The time complexity of the conventional variable stiffness method is approximately \( 7.41 \times 10^8 \) per step, while the average time complexity of the proposed force method is only 2% of that of the conventional method.

In summary, the time complexity of the proposed force method for structural nonlinear analysis is much lower than that of the conventional variable stiffness method. In this regard, the magnitude of the number of plastic degrees of freedom generated is related to the form of the structure and the seismic strength. The size of the region in which the structure enters plasticity is going to differ from the results of this calculation in different cases but is generally smaller. A comparison of the calculation times for the two methods is included in Table 3.

![Figure 5: Maximum gravitational linkage pattern of regional logistics spatial linkages.](image)

![Figure 6: Structure of the logistics spatial linkage network in the Yangtze River Economic Belt.](image)
It can be seen that the time complexity and computation time of the proposed force method are much less than those of the traditional variable stiffness method. But the two have slightly different impact laws for 2 reasons: (1) The time complexity is calculated by considering only the computational effort to solve for the nodal displacements and ignoring the computational effort for secondary parts such as stiffness matrix synthesis. It is assumed that multiplication and division take the same amount of time as addition and subtraction, but in a real computer there is a difference in the computation time between the two. (2) The basic operations analysed in this paper include only the four operations, but when running the program there are also operations such as data initialisation, assignment, reading, and writing. Especially when the amounts of reading and writing are large, the time-consuming process accounts for a large proportion.

7. Conclusions
The thesis proposes a quantitative analysis system of network spatial structure, which is different from the traditional attribute data research idea. The spatial distribution pattern and agglomeration of the air logistics network are described from the perspectives of node spatial location, resource control, relational connectivity, stability, convenience, closeness, and transferability: distribution characteristics, clustering characteristics, connectivity mechanism, and cohesiveness.

The study takes the data of 109 cities in the Yangtze River Economic Belt in 2006, 2011, and 2016 as examples, explores the characteristics of logistics spatial connection between cities and its network structure based on the gravity model, and determines the axis cities and spoke cities in the Yangtze River Economic Belt by using fuzzy clustering algorithm in the perspective of city clusters, analyses the radiation range of each axis city through logistics affiliation, and constructs the axis-spoke logistics network by this means. The formation mechanism of the regional logistics spatial linkage pattern is finally illustrated empirically.

Data Availability
The datasets used in the current study are available from the corresponding author upon reasonable request.
Conflicts of Interest

The authors declare that there are no conflicts of interest.

References


