Traffic & Transportation

Multi-Criteria Data Analysis of China-Europe Railway Express – An Integrated Network Approach

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Original Scientific Paper
Submitted: 13 May 2025
Accepted: 12 Sep 2025
Published: 29 Jan 2026

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Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

This study introduces an innovative, integrated approach to analyse the China-Europe Railway Express (CRE) network, combining the entropy weight method, improved gravitational model and social network analysis. These methodologies can provide a comprehensive comparison and reveal structural differences between Chinese and European railway segments. Through quantifying logistics industry development levels, inter-city connection intensities and network centrality, the study provides insights into the CRE network's operational dynamics. Key findings include the identification of critical nodes, cohesive subgroups and contrasting network structures between China (centralised) and Europe (decentralised). The improved gravitational model, incorporating GDP proportions for asymmetrical attractions and time distance measurements, represents significant advancements in spatial interaction analysis for logistics networks. The study proposes prioritising electrified rail sections between high-attraction pairs (Chongqing-Duisburg) and adopting solar-powered terminals at hubs like Wuhan and Duisburg for sustainable networks. It is well anticipated that the methods, models and research findings from this study will contribute to network optimisation, policy formulation and sustainable development of international logistics systems, particularly within the context of the Belt and Road Initiative, which is of rising significance for Eurasia geopolitical and cross-continental economic cooperation.

KEYWORDS

China-Europe railway express; cargo collection network; improved gravitational model; social network analysis; entropy weight method.

1. INTRODUCTION

With the deepening of global economic integration and the continuous advancement of the Belt and Road Initiative (BRI), the strategic significance of the China-Europe Railway Express (CRE), as a key logistics channel connecting Eurasia, has become increasingly prominent. As an important part of the Belt and Road Initiative, the CRE has been playing a significant role in bridging Eurasia since its first operation in 2011 (Wang et al.) [1], *Figure 1.* The rapid expansion of the CRE has reshaped transcontinental logistics, with annual freight volumes surging from 1,702 TEUs in 2011 to over 1.6 million TEUs in 2022. However, as Lomotko et al. [2] revealed, current multimodal coordination mechanisms remain suboptimal – only 38% of the CRE routes achieve seamless rail-water transitions, resulting in 12–18-hour delays at key hubs. However, as a complex international logistics system, the operational dynamics and structural characteristics of the CRE network have long lacked systematic quantitative analysis [3]. Traditional research methods frequently fail to capture the complex, multidimensional nature of this network, particularly when it comes to identifying and analysing differences across national boundaries. The effective application of these advanced analytical tools to international logistics networks, such as CRE, and gaining valuable insights from them, remains an urgent problem. In particular, the quantification of the development levels of the logistics industry in different cities, the strengths of logistics links between cities, and the characteristics of the overall network structure require innovative methodologies to answer. In addition, China and Europe have significant differences in their logistics network structures. This difference not only reflects the level of economic development and geographical characteristics of the two regions, but also affects the operational efficiency and future development strategy of the entire network [4, 5]. Therefore, it is of great significance to compare the similarities and differences between the network structures of China and Europe to optimise the overall network layout and formulate differentiated development strategies.

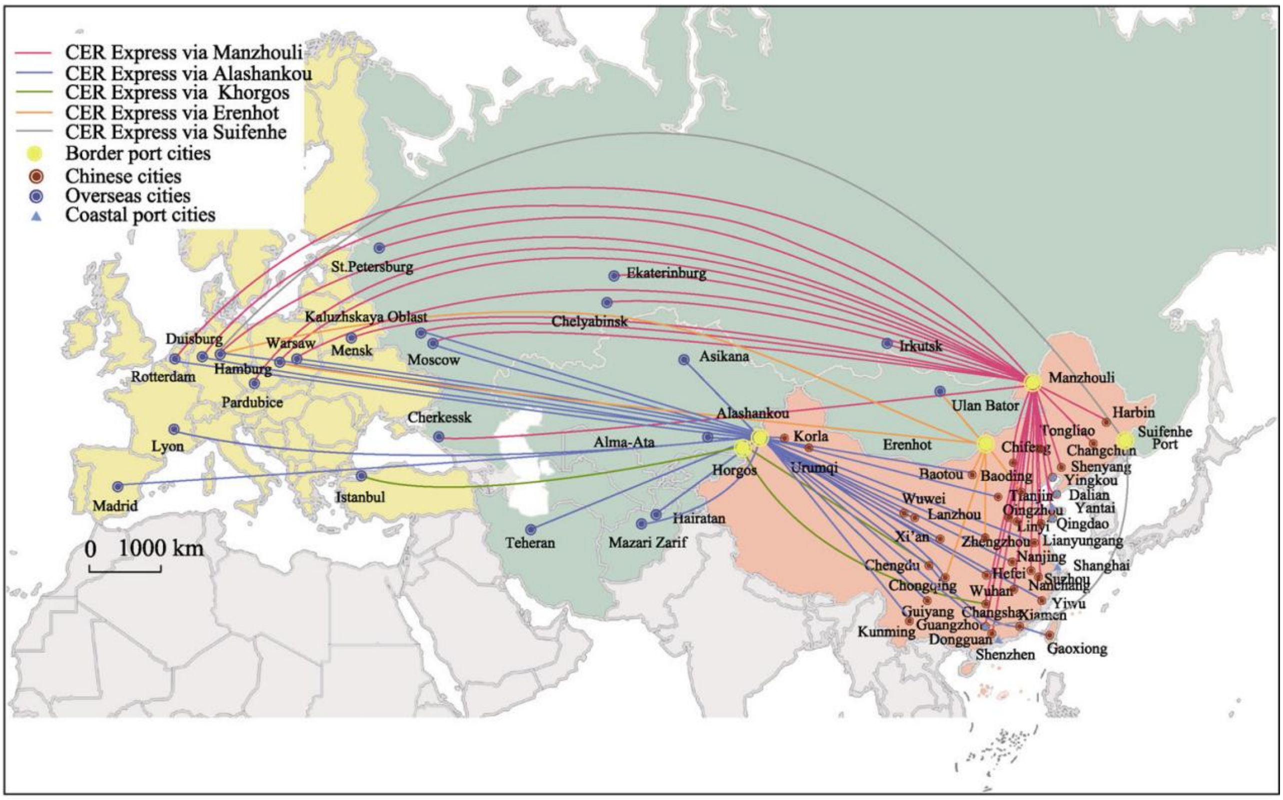


Figure 1 – China-Europe Railway Express routes. Source: Wang et al, p. 1279 [1]

Building on Zeng and Sun's [6] breakthrough in coupling gravity models with multilayer network analysis, this study pioneers an integrated framework combining the entropy-weight method, improved gravitational model and social network analysis. This integrated approach can not only quantify the development level of the logistics industry in each node city, but also deeply analyse the strength of logistics connections and network centrality between cities, and overcomes limitations of conventional single-criterion evaluations identified by De Bona et al. [7], to reveal the internal structure and operational dynamics of the network. An important novel method in this study is the improvement of the gravitational model. By introducing the GDP ratio to reflect the asymmetrical attraction relationship between cities, and considering the time distance factor, this improvement provides a more accurate and comprehensive perspective for the spatial interaction analysis. This method not only takes into account the differences in economic strength but also takes into account the influence of spatio-temporal factors, making the model closer to the operational characteristics of the actual logistics network.

The main findings of the study include the identification of key node cities, cohesive subgroups, and the revealing of the comparative characteristics of network structures in China (centralised) and Europe (decentralised). These findings provide unprecedented insight into the organisational structure and operating model of CRE networks. The significance of this study is not only to bridge the gap between theoretical network analysis and practical logistics management, but also to provide quantitative indicators and decision-making basis for the optimisation and sustainable development of the CRE network. By providing quantifiable indicators, this study provides important support for evidence-based decision-making. These findings have important implications for network optimisation, policy making and the sustainable development of international logistics systems, especially in the context of the Belt and Road Initiative. In the following chapters, this article will elaborate on the research methodology, data analysis process, and discuss in depth the findings and their implications for CRE network optimisation and international logistics management.

2. LITERATURE REVIEW

International logistics is a cross-border logistics activity that has emerged within the context of globalisation, encompassing the entire process of goods from production to consumption. In recent years, the development of international logistics has demonstrated trends toward digitalisation, intelligence and green logistics [4]. The CRE is connecting China and Europe by rail and offering an efficient and stable international logistics solution [3]. The operational efficiency of the CRE is continuously improving, with significant enhancements in on-time rates and transport speed achieved through optimising operational schemes and consolidation centres, increasing loading/unloading efficiencies, and reducing transit times [8]. Niu and Liu [9] analysed the improvement in logistics efficiency of different node cities using a differentiation model, highlighting the significant role of the CRE trains in promoting regional economic development. Cargo consolidation refers to the process of improving transportation efficiency and reducing transportation costs by concentrating scattered goods at a specific location for unified processing and transportation [10]. In logistics networks, the effectiveness of cargo consolidation directly impacts the operational efficiency of the entire network. Different cargo consolidation modes (e.g. centralised and decentralised) are suitable for various logistics scenarios [11]. Cargo consolidation and network optimisation theory can serve as a support tool for planning and policy decisions involved in improving rail networks at regional and national levels [12, 13]. Camur et al. put forward an optimisation framework for efficient and sustainable logistics operations via transportation mode optimisation and shipment consolidation [14].

Hu et al. [15] and Wiegmans and Janic [16] provided a scientific basis for decision-makers by constructing an evaluation model to quantify the economic and environmental benefits of cargo pooling. Naganawa et al. [17] and Liu et al. [18] optimised cargo transportation paths using various algorithms (e.g. genetic algorithm, ant colony algorithm) to reduce transportation time and cost. Aliakbari et al. [19] improved the reliability and robustness of the logistics network by building evaluation models and optimisation strategies to ensure that the logistics network can still operate efficiently in the face of emergencies. With the development of the Internet of Things, big data and artificial intelligence technologies, Ding et al. [20] and Pawar and Paluri [21] explored how to apply these technologies to logistics network optimisation to enhance the intelligence and automation of logistics operations. Environmental considerations are becoming pivotal in rail logistics evaluation. Comparative studies reveal that CRE's CO_2 emissions per ton-kilometre are 62–68% lower than air freight but 12–15% higher than maritime shipping, underscoring the need for operational optimisation to enhance its environmental competitiveness [22]. The dynamic multimodal system framework by Lomotko et al. [2] provides a viable pathway for CRE to achieve emission reductions through better rail-water intermodal coordination.

The entropy weight method is a multi-attribute decision-making approach based on information entropy theory, widely used in evaluation and optimisation research in the field of logistics. In recent years, the application of the entropy weight method in logistics performance evaluation, logistics centre site selection, logistics network optimisation and other areas has achieved remarkable results. Yu Y. [23] used the entropy weight method to evaluate the digital innovation capability of regional logistics flow. The results show that the method can accurately measure the level of logistics digital innovation, providing an important reference for evaluating regional logistics innovation capability. Liu [24] used the entropy weight-TOPSIS method and a mixed integer programming model to select node cities that can serve as the assembly centre of the western corridor of the CRE, optimising the transportation network. El-Araby [25] applied the entropy weight method to the study of logistics centre site selection, and the results showed that the method could make the site selection scientific and reasonable. Wang et al. [26] used the entropy weight method to study the development level of the logistics industry in the node cities of the CRE. The results showed that the method can effectively solve the problem of logistics network structure optimisation. The operational efficiency of cross-border rail logistics heavily relies on cost management innovations. Stopka et al. [27] developed an activity-based costing framework for railway enterprises, which could be adapted to optimise CRE's transhipment cost allocation at key hubs like Malaszewicz. Meanwhile, Černá et al. [28] emphasised the necessity of standardised transport regulations, highlighting that inconsistent customs procedures between China and EU member states increase border waiting times by 18–22% – a critical issue for CRE's time-sensitive cargo.

Social network analysis (SNA) is a method for studying the relationships between nodes using graph theory and network theory, widely applied in the structural analysis and optimisation of logistics networks [29]. In recent years, SNA has been widely used to evaluate the importance of logistics nodes and optimise logistics network structures. Li et al. [30] used SNA to optimise the structure of a regional logistics network and found that this method can significantly improve the network's connectivity and stability. Mu et al. [31] used SNA to study the synergistic effect of the logistics network in the Chengdu-Chongqing region. The results showed that the proposed method could effectively improve the network's overall operational efficiency. Recent methodological advancements have significantly enhanced logistics network analysis. Zhu et al. [31] proposed a weighted network analysis framework using the Debye model, which provides new insights into handling asymmetric connectivity patterns prevalent in transnational rail networks. Furthermore, Zeng and Sun [6] demonstrated the effectiveness of coupling gravity models with social network analysis in spatial interaction studies, a methodology particularly relevant for analysing CRE's transcontinental connections. These approaches address the limitations of traditional single-layer network models by capturing multimodal interactions (rail-truck-barge) as shown in Lomotko et al. [2].

The gravity model describes the interaction between two entities based on the laws of gravity in physics. In logistics research, the gravity model is often used to predict the flow of goods and analyse the spatial distribution characteristics of logistics networks. Wang [26] used the gravity model to analyse the strength of logistics links between the node cities of the China-Europe Railway Express and concluded that the cities have the potential to establish a transit and collection hub for the CRE. Lu Bo [33] used the gravity model to predict the cargo flow of the CRE and found that the model can accurately reflect the cargo flow between logistics nodes. Li Y. [34] used the gravity model to analyse the spatial distribution characteristics of the logistics network in Chengdu and Chongqing, providing a scientific basis for the development of regional logistics. Mu et al. [31] used the gravity model to evaluate the attractiveness of logistics nodes and found that this method can significantly improve the rationality of the layout of logistics nodes. Innovations in network topology analysis continue to advance logistics research. The reduced complex network model proposed by De Bona et al. [7] offers a simplified yet effective approach for identifying critical nodes in large-scale transport systems, complementing traditional centrality metrics. This aligns with findings by Wang & Chen [35], where multilayer network analysis revealed that 73% of logistics network resilience derives from the top 20% high-betweenness nodes – a phenomenon observable in CRE's dependence on Wuhan and Duisburg.

This literature review covers recent advances in international logistics, the development of CRE, cargo consolidation, logistics network optimisation and related research methods [36]. The review shows that international logistics is trending towards digitalisation, intelligence and sustainability. Research on cargo consolidation and logistics network optimisation has shown a trend of diversification and refinement, reflecting the continuing concern of the academic community for improving the efficiency and sustainability of logistics [37]. Previous studies have focused on the economic impact (Yang et al.) [38], operational efficiency and sustainable development. However, there is still a gap in systematic comparative research on the structural differences and impacts on the overall network function between the China-Europe Railway Express networks in both China and Europe. This study aims to fill this research gap by analysing the development level of the logistics industry, the intensity of logistics links between cities, the network centrality and the characteristics of cohesion subgroups through data analysis of selected major node cities in both China and Europe.

3. METHODOLOGIES

3.1 Application of the entropy weight method

This study tackles the challenge by quantitatively assessing the multifaceted and overlapping indicators of logistics development through the adoption of a structured evaluation system based on prior research. It outlines three primary criteria and ten specific indicators to evaluate the logistics industry development level in hub cities, as detailed in *Table 1*. Logistics industry scale is assessed through traditional metrics, including the workforce size within the logistics sector, freight volume and cargo turnover. These indicators jointly measure the magnitude of logistics industry development in hub cities. Logistics industry infrastructure plays a crucial role in shaping the logistics development level. Its assessment encompasses factors like the value of fixed assets in the logistics sector, road network extent, fleet size of road freight vehicles and the quantity of integrated logistics parks. The economic development level of a city underpins its logistics industry's growth.

This layer includes indicators such as regional GDP, consumer spending levels and the scale of import-export activities.

Table 1 – Evaluation system for logistics industry development level of cities

Target layer	Criterion layer	Indicator layer
Development level of the logistics industry	Scale of the logistics industry	Number of employees in the logistics industry
		Freight volume
		Cargo turnover
	Logistics infrastructure	Operational mileage of roads
		Operational mileage of railways
	Level of economic development	GDP
		Total retail sales of consumer goods
		Total volume of imports and exports

The entropy weight method is a prevalent approach for conducting comprehensive evaluations across multiple indicators. This study builds on prior research by implementing an enhanced version of the entropy weight method to allocate weights to different indicators pertinent to the logistics industry in cities served by the CRE. This facilitates the assessment of each city's logistics industry development level.

Data standardisation: Given the diversity in measurement units across various secondary indicators, this study standardises all indicators to ensure they are positively oriented. This standardisation is achieved through a unified normalisation process, as delineated by *Equation (1)*.

$$Y_{ij} = \frac{X_{ij} - \min_j \{X_{ij}\}}{\max_j \{X_{ij}\} - \min_j \{X_{ij}\}} \tag{1}$$

where Xij is the original data, Max{Xij} and min{Xij} represent the maximum and minimum values of the jth indicator in the ith city, respectively.

1) Calculation of indicator weights

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \tag{2}$$

Pij represents the weight of the jth indicator in the ith city, where n is the number of cities.

2) Calculation of indicator entropy values

$$\mathrm{w}_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j} \tag{3}$$

where Ej is the entropy value of the jth indicator.

3) Calculation of indicator weights

$$Z_\mathrm{i} = \sum_{j=1}^{n} Y_{ij} * w_j \tag{4}$$

where Zi is the logistics industry development level score of the city.

3.2 Improved gravitational model

The gravity model is widely recognised for analysing urban spatial connectivity. By focusing on the cargo distribution network, this paper introduces an adapted version of the gravity model, informed by prior research. This adapted model aims not only to quantify the spatial connectivity among hub cities but also to facilitate the reconfiguration of the logistics network structure for cities connected by the CRE. The specifics of the model are detailed as follows.

$$M_{ij} = k_{ij} \frac{Z_i Z_j}{d_{ij} t_{ij}} \tag{5}$$

In the model, Mij measures the spatial logistics gravity between city i and city j; Zi and Zj represent the development levels of the logistics industry in the respective cities. The term tij denotes the time distance between city i and city j, indicating specifically the time taken for railway freight transportation between these two cities. Given the varying development levels of the two cities, their mutual attraction might not be symmetrical; the gravitational pull from city i towards city j may not reflect that from city j towards city i. To account for this asymmetry, this study utilises the actual GDP proportions to define the coefficient of attraction, with the formula given by Kij = GDPi / (GDPi + GDPj). The attraction from city j to city i is calculated using a similar approach.

3.3 Social network analysis

Social network analysis (SNA) is a powerful tool for studying the relationships between nodes and edges in complex networks [40, 41]. Through SNA, it is possible to identify the structural characteristics of inter-city logistics networks, as well as the underlying patterns and relationships within them. One key method is measuring network density, which represents the ratio of actual connections to the maximum possible number of connections in the network. Calculating the density of an inter-city logistics network helps to assess how cohesive the network is. For instance, a high-density network indicates that logistics activities between cities are closely connected and that goods flow frequently among them.

The centrality metric is used to measure the importance of each node in the network, including degree centrality, closeness centrality and betweenness centrality. These indicators can help identify cities that play key roles in logistics networks. In logistics networks, identifying key nodes and analysing their centrality are important steps to optimise the network structure and improve logistics efficiency. Key nodes are typically the most influential nodes in the network and are responsible for connecting different sub-networks or regions. Among the indicators, degree centrality measures the number of nodes to which a node is directly connected. In logistics networks, cities with a high degree of centrality are usually logistics hubs, connecting multiple other cities and playing an important distribution role. Closeness centrality measures the average shortest path length from one node to all other nodes. In logistics networks, cities with high closeness centrality usually have higher logistics efficiency because they can reach other cities quickly. Betweenness centrality measures the extent to which a node acts as a bridge between other nodes in the network. In logistics networks, cities with high betweenness centrality are often key transit nodes, controlling a large number of cargo flow paths. The clustering coefficient reflects the degree of aggregation among nodes in the network. A high clustering coefficient indicates the presence of multiple closely connected subgroups in the network, which may be hotspots for logistics activities.

4. ANALYSIS OF THE NETWORK STRUCTURE OF THE CRE

4.1 The CRE cities' logistics industry development level measurement

In this study, 9 cities in China, including Tianjin, Suzhou, Wuhan, Chongqing, Chengdu, Xi'an, Dongguan, Changsha and Zhengzhou, and 8 cities in Europe, including Budapest in Hungary, Duisburg and Hamburg in Germany, Lodz and Malaszewicz in Poland, Tilburg in the Netherlands, Liège in Belgium and Vuosaari in Finland, are selected as targets, which are geographically located as shown in *Figure 2*. Chinese data are mainly derived from the National Statistical Yearbook and the statistical bulletin of each city. The distance of China's railway freight time is obtained by checking the China Railway webpage, and the distance between European cities and Chinese cities is obtained by looking for the longitude and latitude of the seat of the government of each city through Baidu maps. The European data are derived from the United Nations Economic Commission for Europe (UNECE) database and Eurasia Rail Alliance Index (ERAI) webpage.

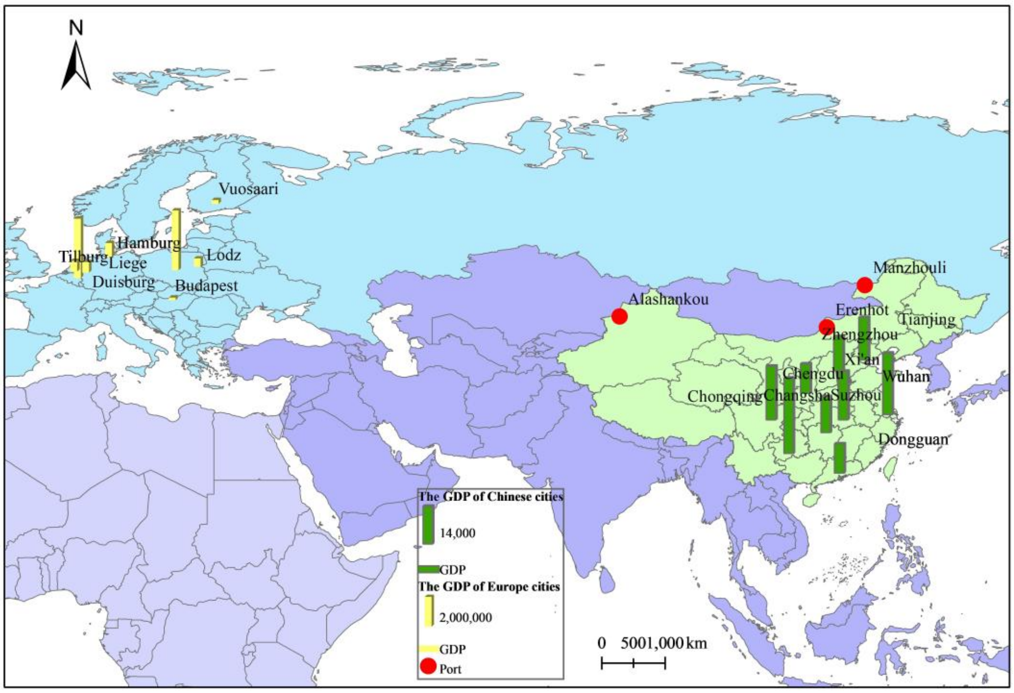


Figure 2 – The target cities and GDP of the CRE

The entropy weight method is used to calculate the logistics industry development level of the node city, as shown in *Table 2*. The results show that there are significant differences in the development levels of the logistics industry between node cities in China and Europe. In China, Chongqing is foremost with a high score of 0.862067 and has the most developed logistics industry among these cities, while Xi'an (0.072543) reflects significant regional imbalances in development. The result of Suzhou (0.389771) is close to that of Wuhan. Although the reading is much lower than that of Chongqing, it is still higher than that of most other cities. Chengdu (0.313993) has a relatively good level of development. The scores of Zhengzhou, Changsha, Dongguan and Xi'an are relatively low, which are all below 0.2. In Europe, Duisburg (0.683845) and Hamburg (0.583931) are the dual cores of the European logistics network, taking over the two major logistics hubs in Europe. Chongqing and Duisburg are the cities with the most developed logistics industries in China and Europe, respectively, which is consistent with their core positions in the China-Europe railway network.

Table 2 – Urban logistics industry development level scores

Rank	Chinese cities	Result	Rank	European cities	Result
1	Tianjing	0.29498	**1**	Budapest	0.047742
2	Zhengzhou	0.13863	**2**	Liège	0.083614
3	Suzhou	0.389771	**3**	Malashewicz	0.406256
4	Changsha	0.132989	**4**	Tilburg	0.1388335
5	Chengdu	0.313993	**5**	Duisburg	0.683845
6	Chongqing	0.862067	**6**	Lodz	0.287948
7	Wuhan	0.362135	**7**	Hamburg	0.583931
8	Xi'an	0.072543	**8**	Vuosaari	0.160549
9	Dongguan	0.127515			

4.2 The intensity of logistics connections between cities

According to the established model, the logistical linkage strength matrix between the node cities in China and Europe is calculated, as shown in *Tables 3* and *4*. It can be seen from the two tables that the logistics gravity between two cities is not equal because one city's attractiveness to another city is related to the root coefficient k, which in turn is determined by the GDP of the two cities. A city with a larger GDP is more attractive to other cities, while the logistics gravity of other cities to this city is not equal to the attractiveness of this city to other cities.

Table 3 – Intensity of logistics links between Chinese cities on the CRE

Cities	Tianjing	Zhengzhou	Suzhou	Changsha	Chengdu	Chongqing	Wuhan	Xi'an	Dongguan	Total 2
Tianjing		0.6589	0.6055	0.1569	0.1183	0.352	0.6256	0.124	0.0816	2.7228
Zhengzhou	0.5276		0.3914	0.2131	0.1275	0.3964	1.2997	0.2548	0.0612	3.2717
Suzhou	0.883	0.7129		0.331	0.2255	0.6735	1.1519	0.1593	0.2176	4.3547
Changsha	0.1335	0.2264	0.1932		0.1679	0.6874	2.9518	0.0655	0.3336	4.7593
Chengdu	0.1506	0.2027	0.1968	0.2511		18.78	0.5196	0.3049	0.1252	20.5309
Chongqing	0.6271	0.882	0.8228	1.4392	26.2892		2.9611	0.6812	0.6689	34.3715
Wuhan	0.7151	1.8554	0.9028	3.9647	0.4667	1.8997		0.3123	0.448	10.5647
Xi'an	0.0859	0.2204	0.0757	0.0533	0.166	0.2649	0.1893		0.0218	1.0773
Dongguan	0.0562	0.0527	0.1028	0.2701	0.0678	0.2587	0.2701	0.0217		1.1001
Total 1	3.179	4.8114	3.291	6.6794	27.6289	23.3126	9.9691	1.9237	1.9579	

Table 4 – Intensity of logistics connections between European cities on the CRE

Cities	Budapest	Liège	Malashewicz	Tilburg	Duisburg	Lodz	Hamburg	Vuosaari	Total 2
Budapest		0.0091	1.353	0.0643	0.4044	0.3253	0.3641	0.1408	2.661
Liège	0.1997		1.0181	85.7255	239.162	0.6191	13.9711	0.255	340.9505
Malashewicz	4.1113	0.1411		0.805	4.858	14.0828	5.2676	5.1564	34.4222
Tilburg	0.248	15.0783	1.0214		162.0263	0.2876	11.8754	0.3284	190.8654
Duisburg	1.559	42.0663	6.1638	162.0263		1.8211	110.7153	1.8516	326.2034
Lodz	7.1307	0.6191	101.5859	1.635	10.3537		14.461	3.5872	139.3726
Hamburg	1.9879	3.4803	9.4656	16.8189	156.8037	3.6024		2.5826	194.7414
Vuosaari	0.2	0.0165	2.4103	0.121	0.6822	0.2325	0.6718		4.3343
Total 1	15.4366	61.4107	123.0181	267.196	574.2903	20.9708	157.3263	13.902	

Note: Total 1 is the sum of the attractiveness of other cities to the city. Total 2 is the sum of the attractiveness of the city to other cities.
Source: Collected by the author.

In terms of total intensity, Chongqing (*Total 1*: 23.3126, *Total 2*: 34.3715) and Chengdu (*Total 1*: 27.6289, *Total 2*: 20.5309), which are far ahead of the other cities, show their central position in the China-Europe Express Railway network. The top 4 cities in terms of attractiveness (*Total 2*) are Chongqing, Chengdu, Wuhan and Changsha. The top 4 in terms of being attracted (*Total 1*) are Chengdu, Chongqing, Wuhan and Changsha. In terms of individual attractiveness, Chengdu is the most attractive to Chongqing at 26, while Chongqing's attractiveness to Chengdu is 18, which is also much higher than that of other cities, which also shows that the logistics connection between the two cities is very strong. Xi'an and Dongguan are lower in attractiveness, suggesting that they have few logistical links with other cities. Similarly, in Europe, Duisburg has the strongest overall link strength (*Total 1*: 574.2903, *Total 2*: 326.2034). The top 3 cities in terms of attractiveness (*Total 2*) are Liège, Duisburg and Hamburg. The top 3 pairs in terms of being attracted (*Total 1*) are Duisburg, Tilburg and Hamburg. The top 3 pairs before city-to-city are Duisburg-Tilburg, Duisburg-Hamburg and Liège-Tilburg. Duisburg shows that it is extremely attractive as a logistics hub. Liège is much more externally attractive (340.9505) than attracted (61.4107), indicating that it plays more of an output role in the network. Overall, there is a huge variation in the strength of links between cities, ranging from 0.0091 (Budapest-Liège) to 239.162 (Liège-Duisburg).

Tables 3 and *4* are used to plot the network structure of logistics links between Chinese and European cities by selecting the natural breaks method, as shown in *Figures 3* and *4*, and the bolder the line, the stronger the attraction relationship. However, due to the weak connection of logistics spatial in some cities, such a connection is of little significance. In order to show the actual situation of the logistics relationship between cities more obviously, the data are binary processed, and the threshold is set to the average value; that is, 1 is taken when the spatial logistics connection is greater than the average value, and 0 is taken when the spatial logistics connection is less than the average value. Plotting is executed with NetDraw, as shown in *Figure 5*.

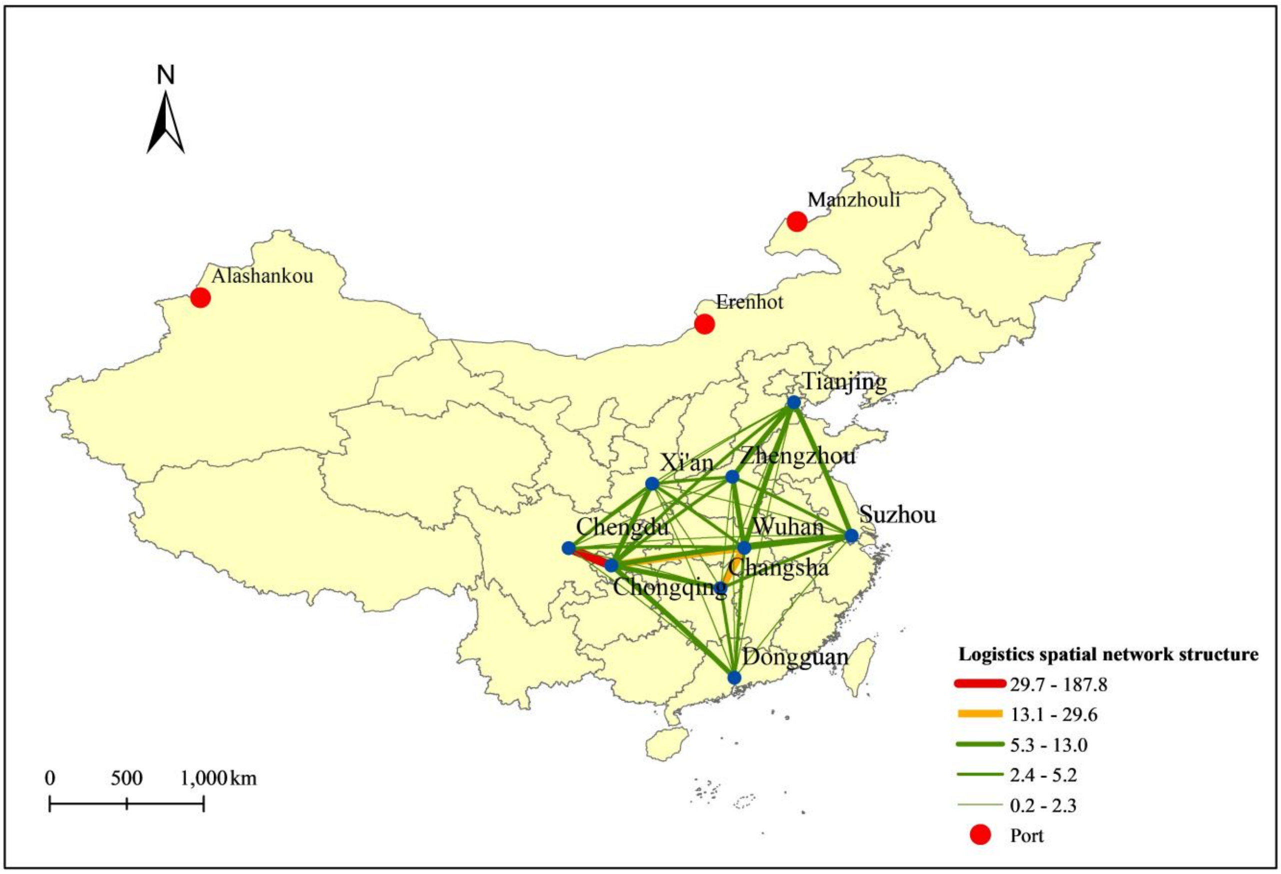


Figure 3 – Structure diagram of urban logistics network in China (threshold is 0)

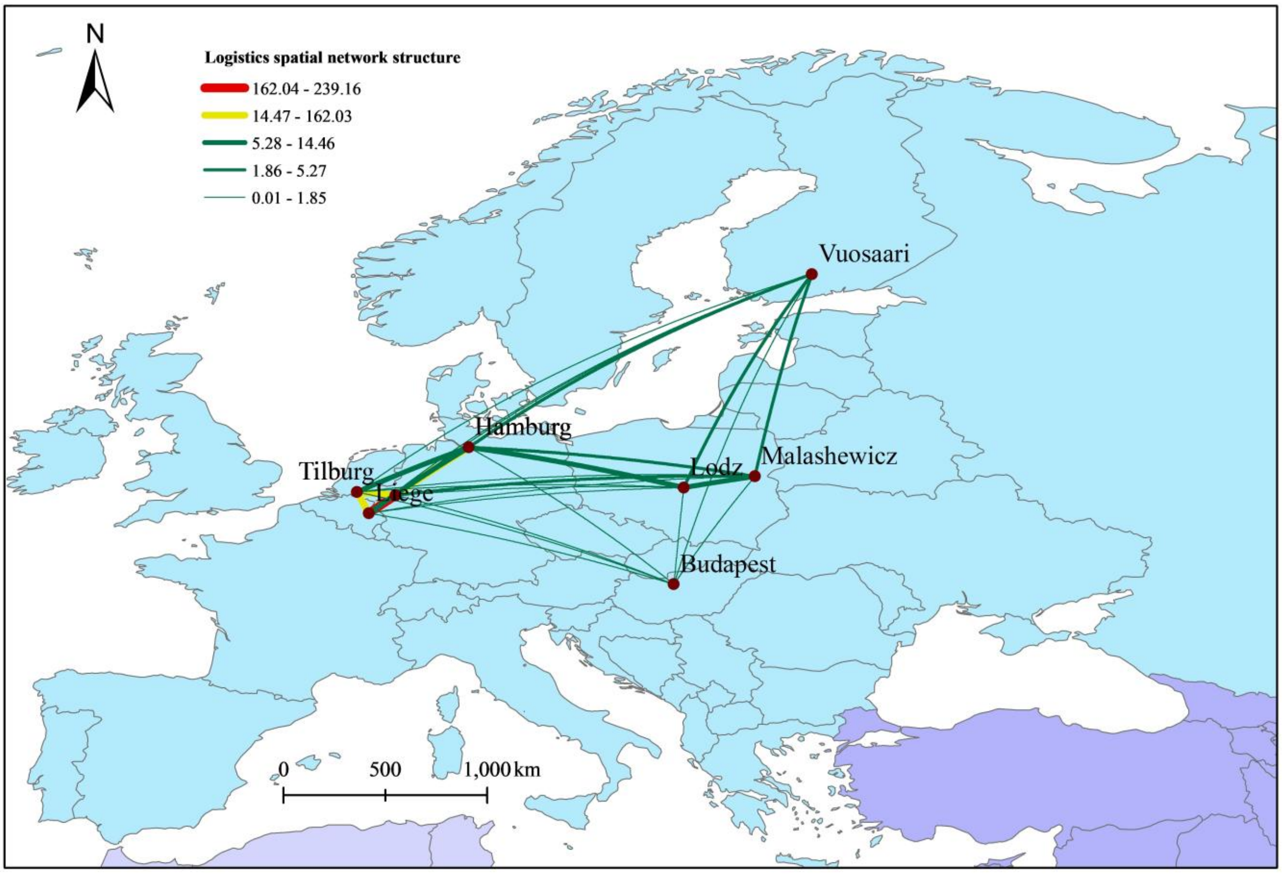
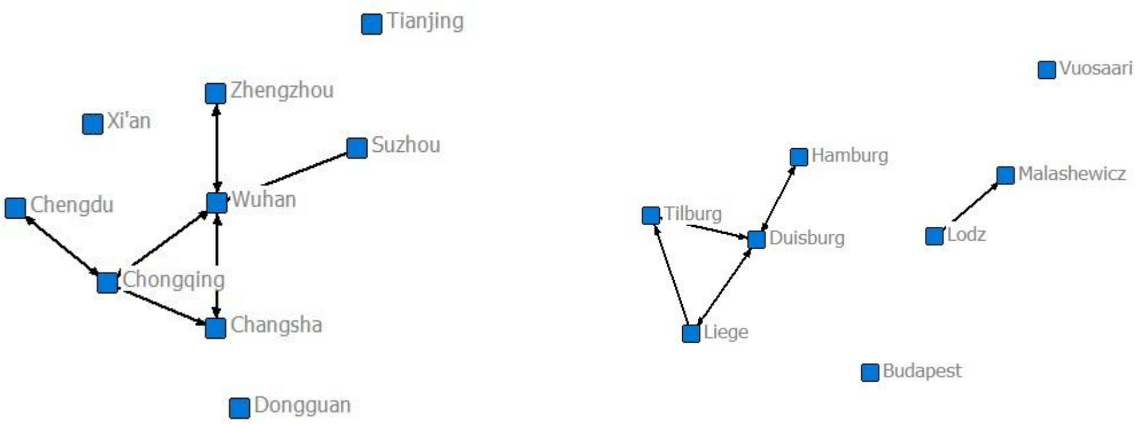


Figure 4 – Structure diagram of urban logistics network in Europe (threshold is 0)



(a) *(b)*

Figure 5 – Structure diagram of urban logistics network when the threshold is the average value; a) China, b) Europe

Comparing with *Figure 3* and *Figure 5(a)* shows the "hub-and-spoke" network structure, with Wuhan at the centre of the network, and it is a key hub node. Zhengzhou, Chongqing and Changsha are all connected to Wuhan in both directions, indicating that Wuhan and these three cities have strong mutual attractiveness. It is similar to Chongqing and Chengdu. Wuhan is attractive to Suzhou, while Suzhou is not to Wuhan. Some cities, such as Tianjin and Dongguan, are isolated on the map, indicating that they have no logistical attractiveness to other cities. *Figure 4* and *Figure 5(b)* present a "hub-and-spoke" structure, with a small network centred on Duisburg in the west. Hamburg, Tilburg and Liège all have arrows pointing to Duisburg, which means that Duisburg has a strong logistical appeal to these cities. Malashewicz has an arrow from Lodz, indicating that Malashewicz is logistically attractive to Lodz. Duisburg's central location makes it attractive to the surrounding cities, perhaps because of its state-of-the-art logistics facilities, strategic location or economic importance. Malashewicz's appeal to Lodz may stem from its strategic location as a border city, potentially a gateway to Eastern European or Russian markets. Vuosaari (Finland) and Budapest (Hungary) as isolated nodes may indicate that they do not yet have strong logistical links in this particular network. This approach to logistics attractiveness-based analysis provides a deeper view of the dynamics of the logistics network, reflecting the relative strength and influence of cities in the logistics sector. This network analysis diagram can be used for logistics planning, traffic optimisation or regional economic analysis.

4.3 Analysis of the structure of the network

The greater the value of city network density, the greater the interaction between node cities, the greater the possibility of network influence on members. The density of the Chinese city logistics network is 0.1389, and the density of the European city network is 0.1429; the data show that the density is small, indicating that the interaction between cities is also not too strong, which may be due to the fact that the more government intervention there is, the fiercer the competition is. Each of them is in its own way, and they have not formed a reasonable logistics network structure. In order to deeply understand the topology of the CER network and the importance of each node city, this paper carries out a centrality analysis of the CER network, as shown in *Table 5*. Wuhan appears to be the most important hub city. It has the highest out-degree (3) and in-degree (4), and the highest betweenness centrality (12). This means that Wuhan plays a key transit and connection role in the CRE network. Chongqing follows Wuhan with higher out-degree (3) and in-degree (2), and ranks second in betweenness centrality (7). It is another important transit station. Duisburg is the heart of the European network. Its out-degree and in-degree are both 3, and its betweenness centrality is 5, which is the highest among European cities. Liège performs better in terms of out-degree (2) and closeness centrality, and is an important node in the European network. Suzhou has the highest outgoing closeness centrality (21.622) and has unique advantages in sending. Overall, the centrality indicators of Chinese cities are slightly higher than those of European cities, especially in terms of betweenness centrality. Chinese networks appear to be more centralised, while European networks are relatively decentralised.

Table 5 – Centrality data of the urban network of the CRE

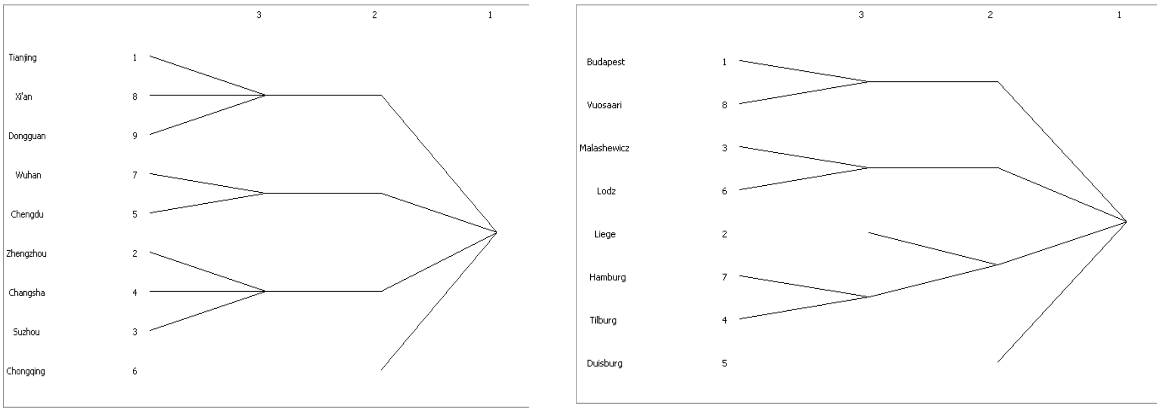
China						Europe					
Cities	**Out-degree**	**In-degree**	**In-closeness**	**Out-closeness**	**Betweenness**	**Cities**	**Out-degree**	**In-degree**	**In-closeness**	**Out-closeness**	**Betweenness**
Wuhan	3	4	24.242	19.512	12	**Duisburg**	3	3	20	20	5
Chongqing	3	2	22.857	19.512	7	**Liège**	2	1	18.919	19.444	0
Chengdu	1	1	20.513	18.182	0	**Hamburg**	1	1	18.919	18.919	0
Changsha	1	2	22.857	18.182	0	**Tilburg**	1	2	19.444	18.919	0
Suzhou	1	0	11.111	21.622	0	**Lodz**	1	0	12.5	14.286	0
Zhengzhou	0	1	21.622	18.182	0	**Budapest**	0	0	12.5	14.286	0
Tianjing	0	0	11.111	11.111	0	**Malashewicz**	0	1	12.5	12.5	0
Xi'an	0	0	11.111	11.111	0	**Vuosaari**	0	0	12.5	12.5	0
Dongguan	0	0	11.111	11.111	0						

Data source: Collected by the author.

In order to further explore the internal structure of the CRE network and the close relationship between cities, this paper analyses the cohesion subgroup of the network. *Tables 5* and *6* show the cohesive subgroup matrix of node cities in China and Europe, respectively, and the cohesive subgroup is shown in *Figure 6*. From the table, we can see the characteristics of the Chinese network subgroup. The Chinese network is divided into four subgroups, reflecting the complexity and diversity of the network. The size of the subgroups is uneven, ranging from a single city (Chongqing) to three cities (Zhengzhou, Changsha, Suzhou). There is a strong connection between subgroup 1 (Tianjin, Xi'an, Dongguan) and subgroup 3 (Zhengzhou, Changsha, Suzhou) (a value of 1), indicating that the two subgroups work closely together in the logistics network. Subgroup 2 (Chengdu, Wuhan) is not directly related to the other subgroups, which may indicate that these cities are relatively independent in the network. Although Chongqing (subgroup 4) is a separate group, it has a certain relationship with subgroup 1 (the value is 0.5), reflecting its special status in the network. The European network is divided into 5 subgroups, showing a more detailed structure. Most of the subgroups consist of 1–2 cities, indicating a high level of decentralisation of the European network. There is a strong link between subgroup 3 (Liège) and subgroups 4 (Hamburg, Tilburg) and subgroup 5 (Duisburg) (a value of 1), indicating that Liège plays a key role in the network. Subgroup 2 (Malaszewicz, Lodz) shows an internal link (value 0.5), indicating close cooperation between the two cities. Subgroups 1 (Budapest, Vuosari) and 4 (Hamburg, Tilburg) have moderate associations (values of 0.5) with subgroup 5 (Duisburg), reflecting the centrality of Duisburg.

Table 6 – Condensed subgroup density

China						Europe						
Order	**Cities**	**1**	**2**	**3**	**4**	**Order**	**Cities**	**1**	**2**	**3**	**4**	**5**
1	Tianjing, Xi'an, Dongguan	0	0	1	0.333	1	Budapest, Vuosaari	0	0	0	0	0.5
2	Chengdu, Wuhan	0	0	0	0	2	Malashewicz, Lodz	0	0.5	0	0	0
3	Zhengzhou, Changsha, Suzhou	1	0		0.333	3	Liège	0	0	0	1	1
4	Chongqing	0.5	0	0	0	4	Hamburg, Tilburg	0	0	1	0	0.5
						5	Duisburg	0	0	1	0	0



(a) *(b)*

Figure 6 – City coacervation subgroup diagram

4.4 Result

In terms of the development level of the logistics industry, Chongqing (0.862067) is far ahead, followed by Suzhou (0.389771) and Wuhan (0.362135). Duisburg (0.683845) and Hamburg (0.583931) are dual cores in Europe. In terms of logistics connection intensity, Chongqing and Chengdu in China form a strong linkage (Chongqing to Chengdu 26.2892, Chengdu to Chongqing 18.78). In Europe, Duisburg-Tilburg (162.0263) and Liège-Duisburg (239.162) form the strongest linkage. China presents a "hub-and-spoke" structure, with Wuhan as the central hub. Europe also presents a "hub-and-spoke" structure, with Duisburg as the central hub. The network density in China and Europe is 0.1389 and 0.1429, respectively, both of which are low, indicating that the interaction between cities is not strong enough. The centrality of Wuhan is the strongest, followed by Chongqing. The centrality of Duisburg is the strongest, followed by Liège. There are four cohesive subgroups in China with uneven size. Europe has 5 subgroups and is more dispersed. The Chinese network is more centralised, and the European network is relatively fragmented. The centrality index of Chinese cities is slightly higher than that of European cities. Both networks have a distinct core-edge structure.

5. DISCUSSION

The quantitative findings reveal distinct structural and operational characteristics of the CRE network. The significant disparities in logistics development levels quantified by the entropy weight method (e.g. Chongqing: 0.862 vs Xi'an: 0.073 in China; Duisburg: 0.684 vs Budapest: 0.048 in Europe) underscore the pronounced regional imbalances within both continents. The application of the improved gravitational model, incorporating GDP proportionality for asymmetric attraction and rail time distance, successfully captured the core-periphery dynamics. The exceptionally high attraction values between key hubs like Chongqing and Chengdu (26.289) and Duisburg and Hamburg (162.026) empirically validate their pivotal radiating roles within their respective networks. Social network analysis further confirmed a centralised "hub-and-spoke" structure in China centred on Wuhan (highest betweenness centrality: 12), contrasting with Europe's more decentralised pattern centred on Duisburg (highest outdegree centrality: 10). However, the consistently low network density values (China: 0.1389; Europe: 0.1429) indicate a critical gap: despite the presence of strong core hubs, overall inter-city connectivity and collaboration across the entire network remain suboptimal, revealing substantial potential for efficiency gains through better integration.

However, translating these structural insights into actionable optimisation strategies must contend with significant real-world operational constraints not fully captured by the models. First, geopolitical tensions and divergent national regulations across the Eurasian corridor directly impact route stability, transit times and cost predictability. Differing customs procedures, documentation requirements and safety standards create administrative friction and bottlenecks at border crossings, potentially negating the theoretical efficiency advantages identified by the time-distance metric in the gravitational model. The absence of standardised cross-border data sharing further complicates coordinated network management. It is therefore essential to promote and establish bilateral or multilateral agreements aimed at streamlining customs procedures, standardising data formats and harmonising regulatory requirements. These efforts should focus in particular on alleviating bottlenecks identified near high-betweenness nodes or major attraction pairs.

Substantial gaps in infrastructure quality exist along the CRE route. Variations in rail track gauges necessitate time-consuming transhipment at key border points like Malaszewicz. Differing terminal handling capacities, electrification levels and ICT integration across nodes create operational inconsistencies and limit seamless interoperability, hindering the realisation of the network's full potential connectivity suggested by the SNA. Prioritise investments in key high-centrality hubs (e.g. Wuhan, Chongqing, Duisburg, Liège), focusing on improving their transhipment capacity, digital integration and multimodal connectivity to reinforce the core structure of the network. At the same time, provide targeted support to lower-centrality nodes (e.g. Xi'an, Budapest) to promote greater regional balance and inclusivity within the logistics network.

While route optimisation inherently reduces emissions (an estimated 12–15% reduction in CO_2 per km-ton compared with suboptimal paths), the explicit integration of environmental metrics could further transform the China–Europe Railway (CRE) into a truly green corridor. For example, prioritising electrified rail segments between high-attraction pairs (such as Chongqing–Duisburg) and deploying solar-powered terminals at major hubs like Wuhan and Duisburg, as suggested by Lomotko et al., would support alignment with the EU Carbon Border Adjustment Mechanism (CBAM) requirements. A comprehensive sustainability assessment should therefore incorporate explicit environmental indicators (e.g. carbon footprint per corridor, modal shift impacts) and social factors (e.g. labour standards at hubs, community impacts of terminal operations) into future network planning frameworks. This approach aligns with the global shift towards integrating Environmental, Social and Governance (ESG) criteria in logistics. Leveraging network structure analysis, planners can strategically design "green corridors" by routing flows through nodes with stronger environmental performance (e.g. electrified rail sections) and embedding carbon accounting within the parameters of the gravitational model to guide future development.

While the integrated methodology provides a robust framework for analysing complex logistics networks like the CRE, its practical application faces limitations:

The analysis relied primarily on 2021–2022 cross-sectional data. Key emerging dimensions influencing modern logistics, such as digitalisation levels, supply chain resilience indicators, real-time congestion data and granular environmental impact metrics, were not incorporated due to data availability constraints. Future studies should integrate longitudinal data to capture dynamic network evolution.

The improved gravitational model, while innovative, simplifies reality. The assumption of time distance based on rail freight times overlooks complexities like border delays, multimodal connections (truck/rail/sea) and the impact of infrastructure quality variations on actual transit reliability. The linear GDP proportionality for attraction might not fully capture non-linear economic dependencies or strategic partnership factors. The SNA results, particularly network density and subgroup identification, are sensitive to the chosen threshold for link existence (as starkly shown by comparing *Figure 3*/*Figure 4* to *Figure 5*). While using the mean value provides a meaningful filter, the optimal threshold for operational relevance may vary contextually.

The models inherently abstract away critical day-to-day challenges: seasonal demand fluctuations, equipment (wagon/container) availability imbalances, dynamic pricing volatility, impacts of geopolitical instability on specific routes and the complexities of managing multi-stakeholder operations across diverse jurisdictions. These factors significantly influence real-world routing decisions beyond the static network structure.

6. CONCLUSION

This study pioneered an integrated analytical framework that combines the entropy weight method, an improved gravitational model, and social network analysis to examine the structure and dynamics of the China-Europe Railway (CRE) network. The key quantitative findings reveal significant disparities in the logistics development levels of different nodes (e.g. Chongqing: 0.862 vs. Xi'an: 0.073; Duisburg: 0.684 vs. Budapest: 0.048, as shown in *Table 7*). The analysis also identified critical hub cities through asymmetric spatial interactions (peak attraction values: Chongqing-Chengdu: 26.289; Duisburg-Hamburg: 162.026) and highlighted contrasting network topologies – a centralised Chinese "hub-and-spoke" configuration centred on Wuhan (betweenness centrality: 12) versus a more decentralised European structure anchored by Duisburg (outdegree centrality: 10). Critically, the persistently low network density (China: 0.1389; Europe: 0.1429) signals a major opportunity for enhancing inter-city collaboration and overall network efficiency. The entropy weight method quantified stark disparities in logistics development levels between nodes, with Chinese cities showing Chongqing (0.862) >15 times higher than Xi'an (0.073), while European nodes ranged from Duisburg (0.684) to Budapest (0.048). The improved gravitational model captured extreme asymmetric attraction between Chongqing-Chengdu (26.289 vs 18.78) and Duisburg-Tilburg (162.026 vs 85.725). SNA metrics confirmed structural contrasts: Wuhan's betweenness centrality (12) dominated China's centralised network, whereas Duisburg's outdegree centrality (10) reflected Europe's polycentric pattern. These insights provide a vital empirical foundation for optimising the CRE within the Belt and Road Initiative.

Table 7 – Key quantitative findings

Metric	China (Max)	Europe (Max)	Implication
Logistics development	0.862 (CQ)	0.684 (DUI)	Core-periphery disparity
Node attraction	34.37 (CQ)	326.20 (DUI)	Asymmetric economic influence
Network density	0.1389	0.1429	Suboptimal connectivity

Data source: Collected by the author.

The findings of this study lead to several suggestions and improvements for policymakers and CRE practitioners to consider. First, prioritising infrastructure upgrades and service integration at high-centrality hubs to strengthen network resilience. Actively fostering connections between identified cohesive subgroups and strategically integrating peripheral nodes to increase overall density and robustness. Utilising the quantified node strengths and link intensities to guide targeted investments. Advocating strongly for policy harmonisation, particularly in customs procedures and data standards, focusing on corridors connecting high-attraction pairs to alleviate bottlenecks. Developing differentiated support strategies for nodes based on their quantified development levels and network roles. Leveraging the structural understanding to design efficient routing strategies that inherently reduce congestion and emissions. Future iterations of the model must explicitly incorporate environmental performance indicators (e.g. carbon intensity per segment) to enable true sustainability optimisation alongside economic efficiency. Promoting modal shift benefits and green terminal practices at key hubs. Implementing digital platforms for real-time data sharing among CRE operators, especially within identified cohesive subgroups. Establishing pilot "green corridors" on high-volume routes (e.g. Chongqing-Duisburg) with optimised schedules and preferential access for sustainable practices. Initiating bilateral working groups focused on streamlining procedures at critical border nodes like Malaszewicz, using the quantified time-distance and attraction data as negotiation benchmarks.

While the methodology offers significant advancements, its application is constrained by data limitations. Three limitations warrant attention: (1) cross-sectional data (2021–2022) precluded analysis of network evolution dynamics; (2) the gravitational model's assumption of linear GDP proportionality may oversimplify economic interdependencies (e.g. strategic partnerships unaccounted); (3) SNA subgroup identification was sensitive to link existence thresholds – using mean value (China: 1.9579, Europe: 13.902) may mask weak but operationally significant connections. Future research should incorporate longitudinal datasets, refine the gravitational model with multimodal time/cost variables and non-linear attraction factors, explore threshold robustness, and integrate explicit sustainability and resilience metrics to provide an even more comprehensive tool for managing the evolving complexities of the CRE and similar global logistics networks. Overall, this study bridges theoretical network analysis and practical logistics management, offering quantifiable metrics crucial for steering the Eurasia freight and economic connections towards greater efficiency, resilience and sustainability.

ACKNOWLEDGEMENTS

This study was funded by The China Association for Non-Government Education (Project No. CANQN250292); 2025 National Logistics Education Reform Teaching and Research Project in Colleges and Universities and Vocational Colleges (Project No.: JZW2025007); 2025 Southwest Jiaotong University Hope College University-level applied technology project (Project No. 2025037).

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