The Evolution of China’s Railway Network (CRN) 1999-2019: Urbanization Impact and Regional Connectivity

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Abstract With the rapid development of China’s economy and society, China’s railway transportation system has been dramatically improved in terms of its scale and operational efficiency. To uncover the underlying relationship between urbanization and railway network structure, this paper examines the evolution of China’s railway transportation system from 1999 to 2019 by applying complex network theory. The results show that China’s railway network (CRN) has become more connected, more “small-world” and more heterogeneous since the beginning of the twenty-first century. Based on the train flow and train travel distance, the evolutionary course of CRN is found to undergo two apparent stages, with a turning point in 2007. By calculating the regional railway connection index (RRCI), it is revealed that the planned core cities in different regions act as bridges connecting the regions to the rest of the whole network.

Keywords China’s Railway Network · Complex network · Network topology · Train flow · Travel distance · Regional connectivity

1 Introduction

Railways, characterized by high capacity, solid travel time reliability, relatively cheap fares, and low carbon emissions, are closely associated with a country’s socioeconomic development and have received considerable attention from scientists in statistics [1], geography [2], transportation [3], and other research fields. As a system of complicated connections of hundreds of cities, the structure of the railway network is affected by a variety of factors, such as political policy, regional population, and geographic conditions, and therefore is commonly studied as a typical complex system. In recent years, the widely used complex network theory [4–6] has developed into a powerful tool to analyze the network performance for different transportation modes, including aviation [7–9], roads [10, 11], and shipping [12–14], and also provides a new perspective for understanding how railway transportation systems work. A series of related studies have investigated topological structure, traffic behavior, and cascading failure on continental [15], national [16, 17], and urban scales [18, 19], respectively. Sen et al. studied the structural properties of the Indian railway network (IRN) and showed that the IRN is endowed with small-world property [20]. Further, Ghosh et al. found that the traffic flow of the railway network is related to its topological characteristics. They investigated the IRN as a weighted complex network and revealed that traffic is accumulated in stations with high connectivity and the links between them [21]. Various literature has emerged relating to the...
analysis of China’s railway network (CRN). Li and Cai studied the CRN [22] and showed that in addition to a common small-world feature, CRN is characterized by other striking structural properties including scale-free distributions, heterogeneous connectivity, and hierarchical modularity. These properties may give rise to particular network vulnerability when important nodes are destroyed [23]. There are also studies focusing on urban railway networks. To understand their complex characteristics, various network measures have been developed. Proposing three network reliability indicators, Liu et al. [24] found that Wuhan’s subway network is susceptible to the failure of important stations, with the geographically central stations playing a significant role in maintaining network reliability. To [25] introduced five centrality measures to conduct network analysis of Hong Kong’s urban rail system and reported that betweenness centrality showed superior performance in reflecting the transport loadings of a rail station. To further distinguish the difference in rail line technology, Sharav et al. [26] extended the basic network measures by adding weights to compare different transit modes. Focusing on the newly built metro networks, Zhao et al. [27] examined the relationships among statistical parameters such as travel cost, chessboard coefficient, and vulnerability in second-tier cities.

Evolutionary analysis of transportation systems has also been a popular research direction [28, 29]. As the expansion of railways plays an important role in shaping the transportation structures of countries, regions, and cities, the dynamic evolution process of railway networks has drawn increasing attention. Marti-Henneberg [30] analyzed the evolution of railways in Europe from 1840 to 2010 on the basis of the railway lines in service and the changes in state economic geography. It was revealed that every national railway network has exhibited unique characteristics even though they have similar guidelines. Murayama [31] measured the time-based connectivity of the Japanese railway network (JRN) using a time-distance matrix to explore how the nationwide expansion of the JRN achieved a time-shrinking effect during 1868-1990 and showed that travel time was reduced by 80% over the course of the century. Moreover, they pointed out that the cities connected by high-speed lines had the most significant gains. The evolution of CRN has also been widely studied as China has experienced a period of rapid CRN development in recent decades. Wang et al. [32] examined the expansion of CRN in the twentieth century and revealed an evolutionary process from “preliminary construction” to “deep intensification”. Further, Jiao et al. [33] adopted three centrality indicators with regard to network topology to examine the changes in node connectivity in China’s high-speed rail network from 2003 to 2014 and showed that network connectivity was significantly improved. Xu et al. [34] proposed a connectivity-accessibility index to assess the impact of the future railway network structure on the potential development of cities. The results show that cities in the Yangtze River Delta would suffer the most, whereas cities in the central and western regions would gain the most.

Although progress has been made in investigating the evolution of CRN, previous studies are mostly concentrated on the evolution law of the network structure. It is generally known the many parts of China differ in geographic settings, economic bases, and population [35]. CRN establishes connections among cities and thus presents specific attributes in economic geography. Studying the complex coupling relationship would be helpful to further explore the major influence of unique demographic and geographical attributes and reveal the underlying mechanism of CRN evolution in detail. In this context, we aim to investigate the evolutive characteristics of the entire CRN by combining the structural topology with the traffic dynamics during the period from 1999 to 2019. The development of high-speed trains allows for stronger spatial interaction of cities and redistribution of economic activities within regions. Finally, we explore the evolution of connections at regional levels and analyze the similarities and differences among different regions.

In summary, a number of scholars have applied complex network theory to explore the structure and dynamics of different transportation networks. Existing literature related to railway networks mainly focuses on characteristics of static networks. Little attention has been paid to the evolution of regional railway internal/external interactions over the long term. Table 1 shows a comparison between our work and existing literature. The major contributions of this paper are as follows: (1) We explore the underlying relationship between urbanization and railway network structure by integrated analysis of network topology and train flows. (2) A regional railway connection index is proposed to uncover regional evolution processes of CRN. We hope that our work will contribute to a better understanding of CRN and provide a reference for evolution analyses of other transportation networks.

The rest of this paper is organized as follows. In Sect. 2, a statistical description of the railway transportation industry is presented. A national-scale evolution analysis of CRN including topological properties, train flows, and geographical properties is given in Sect. 3. Section 4 examines the regional evolution characteristics of CRN, and a conclusion is drawn in Sect. 5.
## Table 1  Comparison between our work and existing literatures

| Publications | Network types | Time span | Research content | Traffic flow | Urbanization impact | Regional connectivity |
|--------------|---------------|-----------|------------------|--------------|---------------------|-----------------------|
| Calzada-Infante et al. (2020) [15] | Static | 2018 | European railway network | Train frequency | City | – |
| Wang et al. (2020) [16] | Static | 2016 | China’s railway network | Number of trains | City, region | Intra-region/inter-region time-based accessibility index |
| Cao et al. (2019) [17] | Static | 2017 | China’s high-speed railway network | Train frequency | City | – |
| Sen et al. (2003) [20] | Static | – | Indian railway network | – | – | – |
| Ghosh et al. (2011) [21] | Static | 2010 | Indian railway network | Number of trains | City, region | – |
| Li et al. (2007) [22] | Static | – | China’s railway network | Number of trains | – | – |
| Ouyang et al. (2014) [23] | Static | – | China’s railway network | Number of trains | – | – |
| Latora et al. (2002) [18] | Static | – | Boston subway network | – | – | – |
| Xu et al. (2016) [36] | Static | 2014 | Beijing urban rail network | Number of passengers | City | – |
| Li et al. (2019) [19] | Static | 2016 | Beijing urban rail network | Number of passengers | – | – |
| Tian et al. (2018) [37] | Static | – | Urban bus network | – | City | – |
| Yue et al. (2019) [38] | Static | 2017 | Railway-coach coupled network | Number of passengers | City, region | Intra-region/inter-region distance-based proximity index |
| Feng et al. (2021) [39] | Static | 2020 | Railway-airline coupled network | Number of trains/flights | City, region | – |
| Zhang et al. (2010) [28] | Dynamic | 1950-2008 | China’s airline network | Number of passengers/cargos | City | – |
| Gallotti et al. (2015) [29] | Dynamic | 18-24 October 2010 | UK public transport network | – | – | – |
| Wang et al. (2009) [32] | Dynamic | 1906-2000 | China’s railway network | Number of passengers/cargos | City, region | – |
| Jiao et al. (2017) [33] | Dynamic | 2003-2014 | China’s high-speed railway network | Train frequency | City | – |
| Xu et al. (2018) [34] | Dynamic | 2007-2030 | China’s high-speed railway network | – | City, region | – |
| Huang et al. (2018) [40] | Dynamic | 2008-2017 | China’s high-speed railway network | Number of trains | City | – |
| Feng et al. (2019) [41] | Dynamic | 12-18 December 2016 | Paris subway network | Number of trains | – | – |
| Our work | Dynamic | 1999-2019 | China’s railway network | Number of passengers/cargos, number of trains | City, region | Intra-region/inter-region traffic-based connection index |
2 Overview of China’s Railway Development

Over the past few decades, China’s railway system has made great strides. Figure 1a shows the expansion of China’s railway system over the period 1949-2019, with two distinct phases. Figure 1b shows the spatial distributions of railway lines in 1999, 2009, and 2019. In 1999, the total railway operation length reached 67,400 km [42], which was approximately twice that in 1949, and ranked first in Asia and fourth in the world [42]. As of 2009, the total length of railway lines exceeded 85,000 km [43], ranking second in the world [43]. At the same time, with an increasing emphasis on the planned construction of high-speed rail (HSR), China started to build HSR lines in the eastern area, and over the following 10 years shaped the national HSR network comprising eight vertical (north-south) and eight horizontal (west-east) corridors. In 2019, although the number of cities linked by conventional railway was not significantly increased, more cities were covered by the HSR with efficient transportation services.

From a macroeconomic perspective, we analyze the changing railway traffic (passengers and cargos) and their association with economic growth [44]. In Fig. 2, it is observed that passenger transport volume has generally grown year by year (an average annual increase of 6.83%). In particular, it experienced more rapid growth from 2009 onward (an average annual increase of 9.15%), which is mainly attributed to the HSR (marked by red). The HSR has become a major transportation mode for medium/long-distance passengers, carrying over 60% of total railway passengers in 2019. However, passenger transport volume of the conventional railway (marked by blue) dropped slightly after 2009. Unlike railway passengers, the total railway cargo volume did not show a consistent rise. To be more specific, the growth of cargos stagnated in 2012, dropped significantly in 2015, and started to recover again in 2017. Due to the continuous economic structure adjustment and energy structure optimization, large-quantity cargo traffic (coal, mineral, steel, etc.) initially dropped from 2012 and then rose in the following years. It is also worth mentioning that passenger traffic was greatly affected (7.9% decrease) by the outbreak of severe acute respiratory syndrome (SARS), an infectious disease, in 2003. However, railway cargo traffic appeared unaffected in the same year. Additionally, as shown in Fig. 2c, d, passenger traffic grew almost linearly with gross domestic product (GDP), while cargo traffic did not show a similar tendency.

3 Evolutive Properties of CRN

3.1 Construction of CRN

Typically, the definition of railway network depends on the focused questions in research. Network models can be divided into two main categories: physical networks (e.g.,
Space K [32]) and logical networks (e.g., Space P [20], Space L [22], and Space G [45]). In physical networks, nodes and edges represent real entities in the topological structure, while in logical networks, the topological structures are formed in accordance with some artificially defined rules, and the network elements are partially or totally virtual. We collected railway physical infrastructure data and passenger train schedules for 20 years (1999-2019) to examine the evolution of China’s railway transportation system from the perspective of the logical network. The data set involves 3187 stations and 81,081 train schedules in total in mainland China. In this study, nodes are defined as cities. Multiple stations in the same city have been merged into one node. Two nodes are connected by an edge if they are the starting and ending cities of a train schedule, respectively. The geographical representation of CRN in 1999, 2009, and 2019 is shown in Fig. 3. Obviously, CRN has a progressive tendency to form a denser network with high-traffic links.

3.2 Topological Properties of CRN

This section discusses the evolution of the topological properties of CRN from 1999 to 2019 (see Table 2). In general, CRN increased significantly in that time period despite some fluctuations. Specifically, the number of nodes increased by 21.68% from 226 in 1999 to 275 in 2019; edges increased by 83.72% from 682 in 1999 to 1253 in 2019. The average degree continued to grow, which means that CRN was more closely connected in the same period. The increase in clustering coefficient and the reduction in average shortest path length indicate more prominent small-world properties. Furthermore, the decreased assortativity coefficient with a negative value implies CRN’s higher disassortative level and more heterogeneous network structure. Based on measurements of these network topology indices, CRN was more densely reticulated, more “small-world”, and more heterogeneous across that period.
The network topology in 1999, 2009, and 2019 is further evaluated in Fig. 4. Cumulative degree distribution, one of the most important properties, is measured and shown in Fig. 4a. It follows a two-regime power law during the 3 years, indicating a common phenomenon, namely an inhomogeneous connectivity distribution, where a minor fraction of nodes hold many connections, while most nodes have only sparse connections [46]. Additionally, the “two-regime” inflection points are progressively right-shifted ($k_{1999} = 15$, $k_{2009} = 20$, $k_{2019} = 26$). Interestingly, cities with a degree larger than that of the inflection points are usually municipalities, provincial capitals, and sub-provincial cities. In particular, Shenzhen was included in the high-degree group in 2009, and Fuzhou, Xiamen, and Ningbo were included in 2019. Betweenness, a popular topological index, is widely used to quantify node transitivity in an overall network. The calculation of betweenness is equal to the fraction of all shortest paths passing through a given node. Figure 4b shows the relation between degree (i.e., the number of connections) and node color reflects node strength (i.e., the number of departing or arriving trains). Both thickness and color of edges represent the weight of edges (i.e., train flow).

Table 2 Evolution of topological parameters of CRN from 1999 to 2019

| Year | $N$  | $E$  | $\langle k \rangle$ | $C$   | $d$  | $D$  | $r$   |
|------|------|------|---------------------|-------|------|------|-------|
| 1999 | 226  | 682  | 6.04                | 0.329 | 3.04 | 7    | -0.062|
| 2001 | 216  | 717  | 6.64                | 0.398 | 2.91 | 6    | -0.089|
| 2003 | 212  | 709  | 6.68                | 0.375 | 2.91 | 6    | -0.104|
| 2005 | 212  | 716  | 6.75                | 0.387 | 2.85 | 6    | -0.121|
| 2007 | 214  | 738  | 6.90                | 0.389 | 2.78 | 6    | -0.173|
| 2009 | 229  | 837  | 7.31                | 0.400 | 2.79 | 7    | -0.17  |
| 2011 | 236  | 854  | 7.24                | 0.426 | 2.77 | 7    | -0.175 |
| 2013 | 234  | 886  | 7.57                | 0.419 | 2.77 | 6    | -0.179 |
| 2015 | 252  | 1027 | 8.15                | 0.480 | 2.71 | 6    | -0.177 |
| 2017 | 271  | 1193 | 8.80                | 0.508 | 2.63 | 6    | -0.205 |
| 2019 | 275  | 1253 | 9.11                | 0.516 | 2.62 | 5    | -0.204 |

$N$ represents the number of nodes. $E$ represents the number of edges. $\langle k \rangle$ means an average degree. $C$ is the overall level of the clustering coefficient in the network. $d$ is the average shortest path length of the entire network, and $D$ is the diameter. $r$ is the assortativity coefficient ranging between -1 and 1.

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3.3 Evolution of the Train Flow and Train Travel Distance

The train flow between cities is always constrained by travel distance. Technological innovations in the rail sector have brought a shrinkage of space and influenced spatial interactions among cities [33]. For a deeper understanding of the functional properties of CRN, the relationship between train flow and train travel distance is analyzed. As Fig. 5a shows, the edges with train travel distances within 300 km accounted for 41.92% in 1999. Nevertheless, the percentage decreased by 12% in 2009 and continued to decline by 5.7% in 2019. This suggests that a larger portion of trains performed long-distance transport tasks owing to high-speed rail technology. Figure 5b exhibits the evolution of the cumulative probability of train flow over train travel distance from 1999 to 2019. The thresholds of distances with 80% of the train flows are extracted and shown in the inset. From 1999 to 2007, these distance thresholds increased significantly, whereas they remained relatively stable after 2007, when high-speed trains started to be put into service and became a primary way to satisfy the growing transportation demand. One interesting point is that high-speed trains did not continue to facilitate the establishment of more new connections among long-distance nodes, instead they mainly increased the train flow of existing connections.

The train flow between different city pairs is further studied to reveal the year-by-year evolution of CRN. Table 3 tabulates the top 20 edges with the highest train flow in 1999, 2007, and 2019 (here the year 2007 is selected instead of 2009 since an inflection point appeared in 2007 in Fig. 5b). Municipalities, provincial capitals, and sub-provincial cities are referred to as large cities, and the rest as small cities. More specifically, it can be seen that the edges of Beijing–Tianjin and Guangzhou–Shenzhen consistently appeared and remained the top three during the 3 years. These two edges are respectively distributed in the most developed regions and have a short railway travel distance. From 1999 to 2007, these distance thresholds increased significantly, whereas they remained relatively stable after 2007, when high-speed trains started to be put into service and became a primary way to satisfy the growing transportation demand. One interesting point is that high-speed trains did not continue to facilitate the establishment of more new connections among long-distance nodes, instead they mainly increased the train flow of existing connections.

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average train travel distance of the top 20 edges reached about 408.16 km, which was twice as long as that in 1999. In 2019, although train speed continued to increase, long-haul edges connecting large cities did not maintain a high ranking. It was found that large cities had stronger interactions with their nearby satellite cities, and the average train travel distance of top 20 edges declined compared to 2007. It has been reported that high-speed rail acts as a catalyst in facilitating region integration [48]. This may explain why Changsha–Xiangtan, Changsha–Zhuzhou, and Zhengzhou–Jiaozuo were added to the top 20 list. Figure 6 illustrates the percentage of large city pairs (denoted by the blue line) and the percentage of average train travel distance (denoted by the gray line) of the top 20 edges year by year. In general, the proportion of large city pairs first rose and then declined. We also found that the average train travel distance initially shows an obvious increase before 2007 with the increase in long-haul edges between larger city pairs, and subsequently tends to be relatively stable.

4 Regional Evolution Characteristics of CRN

The evolution of CRN has not only triggered changes in overall railway structure, but has also promoted internal and external connection of regions. We selected 19 regions (i.e., megalopolis, urban agglomeration, or city groups) proposed in the 13th Five-Year Plan [49] as our areas of interest. To evaluate the role a city plays in the regional railway passenger transport, we develop a regional railway connection index (RRCI) \( R_i \) for city \( i \) as the proportion of inside-region train flow \( S_{i-in} \) to outside-region train flow \( S_{i-out} \) as follows.

\[
R_i = \frac{S_{i-in} + 1}{S_{i-out} + 1} \tag{1}
\]

When \( R_i > 1 \), it indicates that city \( i \) has an advantage in connecting cities within the region; when \( R_i < 1 \), it means this city fosters more interactions with cities outside the region. We define a city as a regional internal advantage (RIA) city if its RRCI is greater than 1 and a city as a regional external advantage (REA) city if its RRCI is less than 1.

We utilize both the RRCI and degree ranking to assess a city’s regional role in the dynamics of network topology. As shown in Fig. 7a, the RRCI shows a positive correlation with the degree ranking, meaning that cities with higher degree within region tend to expand their own external connections. High-degree cities are generally planned core cities, which are not only bellwethers of regional development, but also windows to the outside regions. We further show the ratio of the number of RIA cities to the number of REA cities in Fig. 7b. The value initially decreases linearly, and then increases and gradually reaches a plateau.

To better demonstrate the regional dynamics of CRN over time, we plot the spatial distribution of RRCI for 1999, 2007, and 2019 in Fig. 8a, b, c, respectively, where nodes are marked with different colors according to their levels of RRCI. For simplification, we take only the core cities, such as municipalities or provincial capitals, into consideration. Spatially, cities with a low RRCI are mostly distributed in central and western China. In eastern China, this index varies widely across different regions. For the Beijing–Tianjin–Hebei region, the two core cities, Beijing and Tianjin, maintain a stable level of RRCI. Beijing is identified as an REA city with low RRCI, and Tianjin as an RIA city with high RRCI. Compared with the Beijing–
Tianjin–Hebei region, Pearl River Delta behaves quite differently in the RRCI evolution. In 1999, Guangzhou and Shenzhen had the advantage in outer/inner interactions, respectively. With the increasing train flow within this region, Guangzhou strengthened its internal transport advantage and gradually converted into an RIA city with improved RRCI. Shenzhen continued to maintain the status of an RIA city. Subsequently, long-distance high-speed railway lines were gradually launched into service, including Wuhan–Guangzhou high-speed railway in 2009, Beijing–Guangzhou high-speed railway in 2012, and Guiyang–Guangzhou high-speed railway in 2014. The external railway channels of Pearl River Delta were expanded. As a consequence, both Guangzhou and Shenzhen transformed from REA cities into RIA cities. We further analyze the ratio of RIA/REA cities (referred to as RIE) in the Beijing–Tian–Hebei region and Pearl River Delta (see Table 4). It is easy to see that this ratio in

Table 3 Top 20 edges ranked by train flow in 1999, 2007, and 2019

|   | Edge               | Distance (km) | Time saved (h) |   | Edge               | Distance (km) | Time saved (h) |   | Edge               | Distance (km) | Time saved (h) |
|---|--------------------|---------------|----------------|---|--------------------|---------------|----------------|---|--------------------|---------------|----------------|
|1  | Guangzhou–Shenzhen | 111.68        |                |   | Guangzhou–Shenzhen | 111.68        | 0.22           |   | Beijing–Tianjin    | 108.64        | 0.60           |
|2  | Beijing–Tianjin    | 108.64        | 0.83           |   | Shanghai–Nanjing   | 268.12        | 0.38           |   | Guangzhou–Shenzhen | 111.68        | 0.38           |
|3  | Shenyang–Fushun     | 42.84         | 0.08           |   | Beijing–Tianjin    | 108.64        | 0.08           |   | Shanghai–Nanjing   | 268.12        | 0.78           |
|4  | Beijing–Shijiazhuang | 269.29       | 0.66           |   | Shanghai–Hangzhou  | 165.24        | 0.72           |   | Beijing–Shanghai   | 1063.80       | 5.68           |
|5  | Harbin–Qiqihar      | 267.29        |                |   | Beijing–Shijiazhuang | 269.29       | 2.77           |   | Kunming–Dali       | 256.52        | 5.40           |
|6  | Harbin–Suihua       | 102.54        |                |   | Beijing–Qinhuangdao | 269.90       | 1.58           |   | Changchun–Jilin    | 100.58        | 0.92           |
|7  | Harbin–Mudanjian    | 267.36        |                |   | Jinan–Qingdao      | 304.97        | 1.35           |   | Changsha–Xiangtan  | 36.75         | 1.15           |
|8  | Shanghai–Hangzhou   | 165.24        |                |   | Beijing–Shanghai   | 1063.80       | 4.02           |   | Shanghai–Wuhan     | 674.29        | 1.85           |
|9  | Nanchang–Jiujiang  | 116.19        |                |   | Shanghai–Ningbo    | 154.57        | 3.15           |   | Shenyang–Dalian    | 352.55        | 1.83           |
|10 | Qiqihar–Halun Buir | 378.22        |                |   | Beijing–Qingdao    | 545.94        | 8.40           |   | Harbin–Jiamusi     | 310.66        | 4.05           |
|11 | Beijing–Zhangjiakou | 161.31        |                |   | Beijing–Wuhan      | 1049.57       | 3.77           |   | Changsha–Zhuzhou   | 42.24         | 0.63           |
|12 | Harbin–Jilin        | 211.56        |                |   | Chengdu–Chongqing  | 269.93        | 6.88           |   | Zhengzhou–Jiaozuo  | 65.53         | 1.77           |
|13 | Hegang–Jiamusi      | 60.05         |                |   | Shenyang–Dalian    | 352.55        | 0.72           |   | Xi’an–Chengdu       | 607.12        | 12.15          |
|14 | Heihe–Qiqihar       | 411.53        |                |   | Beijing–Handan     | 404.54        | 1.22           |   | Guangzhou–Zhanjiang | 367.20        | 3.57           |
|15 | Jixi–Mudanjian      | 133.63        |                |   | Beijing–Shenyang   | 622.24        | 5.52           |   | Chengdu–Chongqing  | 269.93        | 2.27           |
|16 | Changchun–Jilin     | 100.58        |                |   | Harbin–Qiqihar     | 267.30        | 0.25           |   | Shanghai–Wenzhou   | 371.13        | 5.90           |
|17 | Jiamusi–Shanqiashan | 61.14         |                |   | Beijing–Zhengzhou  | 623.41        | 1.98           |   | Shenyang–Dandong   | 203.71        | 2.38           |
|18 | Liaoyungang–Xuzhou  | 201.84        |                |   | Lianyungang–Xuzhou | 201.84        | 1.07           |   | Changchun–Yanbian  | 355.71        | 5.25           |
|19 | Xi’an–Weinan        | 53.89         |                |   | Guangzhou–Chongqing | 976.06       | 22.87          |   | Guangzhou–Wuhan    | 837.29        | 9.93           |
|20 | Shenyang–Anshan     | 83.08         |                |   | Jixi–Mudanjian     | 133.63        | 0.32           |   | Beijing–Xi’an      | 910.25        | 6.70           |
|   | Average             | 165.40        |                |   | Average            | 408.16        | 3.35           |   | Average            | 365.69        | 3.67           |

Here, edges that appear in the top 20 list in all 3 years are underlined. The municipalities, provincial capitals, and sub-provincial cities are in bold.

including Wuhan–Guangzhou high-speed railway in 2009, Beijing–Guangzhou high-speed railway in 2012, and Guiyang–Guangzhou high-speed railway in 2014. The external railway channels of Pearl River Delta were expanded. As a consequence, both Guangzhou and Shenzhen transformed from REA cities into RIA cities. We further analyze the ratio of RIA/REA cities (referred to as RIE) in the Beijing–Tian–Hebei region and Pearl River Delta (see Table 4). It is easy to see that this ratio in
Beijing–Tianjin–Hebei region is much higher than that in Pearl River Delta. Most cities in the Beijing–Tianjin–Hebei region focus on internal interactions with nearby cities, while a small number of cities show a relatively strong regional bridging effect. In contrast to the Beijing–Tianjin–Hebei region, Pearl River Delta has more REA cities.
5 Conclusion

This paper has analyzed the evolution of CRN over the period 1999-2019 in respect of factors including topological structure, train flow, and train travel distance. By reviewing the development of China’s railway system, we found that both the railway length and passenger traffic demonstrate a continuous increase at a higher rate. Subsequently, based on complex networks theory, we found that CRN has become more densely connected and heterogeneous with increasingly prominent small-world properties over time. The combined analysis of the train flow and train travel distance shows a two-stage evolutionary process, with the turning point in 2007 when high-speed trains started to be put into operation. Additionally, the spatial distribution of high-flow edges exhibited an obvious change. The edges with large train flow gradually infiltrated into large city pairs and then shifted towards the connections between large cities and their nearby small cities. Finally, we propose an RRCI, based on regional internal/external train flow, to identify RIA and REA cities. Cities with high degrees are consistently found to have an advantage in connecting with cities outside the region and are identified as REA cities, whereas cities with low degrees always exhibit strong internal interactions and are identified as RIA cities.

Our analytical approaches and results may contribute to future decision-making and decision evaluation. Importantly, following the proposed framework, the comprehensive impact resulting from the railway planning implementation can be adequately assessed through long-term experimental validation. Based on the evolution results, decision-makers may clearly identify the fast/slow-growing nodes/edges/areas and re-evaluate the effectiveness of previous decisions. Furthermore, due to the applicability of complex network theory for different transportation modes, the proposed approach can also be applied to explore the network evolution of urban rail systems and help to identify spatiotemporal characteristics.

With the continued expansion of intercity and urban rail networks, transportation network features may become more complex. Given the unique characteristics of different rail networks, our future research will focus on the integrated point-to-point travel process based on multilayer complex network theory. We also suggest that additional indicators such as network reliability, economic conditions, and geographical features should be considered in measuring the importance of network facilities for future research.

Appendix A: Acronyms

| Acronyms Description |
|----------------------|
| CRN China’s railway network |
| IRN Indian railway network |
| JRN Japanese railway network |
| HSR High-speed railway |
| RRCI Regional railway connection index |
| RIA Regional internal advantage |
| REA Regional external advantage |
| RIE Ratio of number of RIA cities to that of REA cities |

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References

1. Sienkiewicz J, Holyst JA (2005) Statistical analysis of 22 public transport networks in Poland. Phys Rev E 72:046127
2. Taaffe EJ, Morrill RL, Gould PR (1963) Transport expansion in underdeveloped countries: a comparative analysis. Geogr Rev 53:503–529
3. Rühl A (1991) Financial relations between European railways for their international services. Transp Res Part A 25(4):203–207
4. Watts DJ, Strogatz SH (1998) Collective dynamics of small-world networks. Nature 393:440–442
5. Boccaletti S, Bianconi G, Criado R et al (2014) The structure and dynamics of multiplexer networks. Phys Rep 544(1):1–122
6. Albert R, Barabasi AL (2002) Statistical mechanics of complex networks. Rev Mod Phys 74:47–97
7. Guimera R, Mossa S, Turtschi A et al (2003) The worldwide air transportation network: anomalous centrality, community structure, and cities’ global roles. Proc Natl Acad Sci U S A 102(22):7794–7799
8. Du WB, Zhou XL, Lordan O et al (2016) Analysis of the Chinese Airline Network as multi-layer networks. Transp Res Part E 89:108–116
9. Verma T, Araujo NAM, Herrmann HJ (2014) Revealing the structure of the world airline network. Sci Rep 4:5638
10. Crucitti P, Latora V, Porta S (2006) Centrality measures in spatial networks of urban streets. Phys Rev E 73:036125
11. Badhrudeen M, Derrible S, Verma T et al (2022) A geometric classification of world urban road networks. Urban Sci 6(1):11
12. Hu YH, Zhu DL (2009) Empirical analysis of the worldwide maritime transportation network. Physica A 388(10):2061–2071
13. Calatayud A, Mangan J, Palacin R (2017) Vulnerability of international freight flows to shipping network disruptions: a multiplex network perspective. Transp Res Part E 108:195–208
14. Ducruet C, Notteboom T (2012) The worldwide maritime network of container shipping: spatial structure and regional dynamics. Global Netw 12(3):395–423
15. Calzada-Infante L, Adenso-Diaz B, Carbajal SG (2020) Analysis of the European international railway network and passenger transfers. Chaos Solitons Fractals 141(1):1–10
16. Wang W, Cai KQ, Du WB et al (2020) Analysis of the Chinese railway system as a complex network. Chaos Solitons Fractals 130:109408
17. Cao WW, Feng XN, Zhang H (2019) The structural and spatial properties of the high-speed railway network in China: a complex network perspective. J Rail Transit Plan Manag 9:46–56
18. Latora V, Marchiori M (2002) Is the Boston subway a small-world network? Physica A 314(1–4):109–113
19. Li XL, Zhang P, Zhu GY (2019) Measuring method of node importance of urban rail network based on h index. Appl Sci 9(23):5189
20. Sen P, Daugupta S, Chatterjee A et al (2003) Small-world properties of the Indian Railway network. Phys Rev E 67:036106
21. Ghosh S, Banerjee A, Sharma N, Agarwal S, Ganguly N (2011) Statistical analysis of the Indian Railway network: a complex network approach. Acta Phys Pol B Proc Suppl 4:123–137
22. Li W, Cai X (2007) Empirical analysis of a scale-free railway network in China. Physica A 382:693–703
23. Ouyang M, Zhao LJ, Hong L, Pan PP (2014) Comparisons of complex network based models and real train flow model to analyze Chinese railway vulnerability. Reliab Eng Syst Saf 123:38–46
24. Liu J, Peng QY, Chen JQ, Yin Y (2020) Connectivity reliability on an urban rail transit network from the perspective of passenger travel. Urban Rail Transit 6(1):1–14
25. To WM (2015) Centrality of an urban rail system. Urban Rail Transit 1(4):249–256
26. Sharaf N, Bekhor S, Shifman Y (2018) Network analysis of the Tel Aviv Mass Transit Plan. Urban Rail Transit 4(1):23–34
27. Zhao F, Cao H, Lu TW (2021) What impact will the new-built metro bring to the transportation of second-tier cities? From the perspective of a multilayer complex network. Urban Rail Transit 7:117–127
28. Zhang J, Cao XB, Du WB et al (2010) Evolution of Chinese airport network. Physica A 389(18):3922–3931
29. Gallotti R, Barthelemy M (2015) The multilayer temporal network of public transport in Great Britain. Sci Data 2:140056
30. Marti-Henneberg J (2013) European integration and national models for railway networks (1840–2010). J Transp Geogr 26:126–138
31. Murayama YJ (1994) The impact of railways on accessibility in the Japanese urban system. J Transp Geogr 2:87–100
32. Wang JE, Jin FJ, Mo HH, Wang FH (2009) Spatiotemporal evolution of China’s railway network in the 20th century: an accessibility approach. Transp Res Part A 43:765–778
33. Jiao JJ, Wang JE, Jin FJ (2017) Impacts of high-speed rail lines on the city network in China. J Transp Geogr 60:257–266
34. Xu WT, Zhou JP, Yang LC, Li L (2018) The implications of high-speed rail for Chinese cities: connectivity and accessibility. Transp Res Part A 116:308–326
35. Jin FJ, Ding JX, Wang JE, Liu D, Wang CJ (2012) Transportation development transition in China. Chin Geogr Sci 22:319–333
36. Xu Q, Mao BH, Bai Y et al (2016) Network structure of subway passenger flows. J Stat Mech Theory Exp 3:033404
37. Tian ZW, Zhang Z, Wang HF et al (2018) Complexity analysis on public transport networks of 97 large-and medium-sized cities in China. Int J Mod Phys B 32(9):1850108
38. Yue HQ, Quan QF, Pan YT et al (2019) Detecting clusters over intercity transportation networks using K-shortest paths and hierarchical clustering: a case study of mainland China. Int J Geogr Inf Sci 33(5):1082–1105
39. Feng X, He SW, Li GY et al (2021) Transfer network of high-speed rail and aviation: structure and critical components. Physica A 581:126197
40. Huang YP, Lu SW, Yang XP et al (2018) Exploring railway network dynamics in China from 2008 to 2017. ISPRS Int J Geo Inf 7(8):320
41. Feng X, He SW, Li YB (2019) Temporal characteristics and reliability analysis of railway transportation networks. Transportmetric A Transp Sci 15(2):1825–1847
42. Peng KZ (2000) China railway yearbook. China Railway Publishing House, Beijing
43. Qian M (2010) China railway yearbook. China Railway Publishing House, Beijing
44. Laurino A, Ramella F, Beria P (2015) The economic regulation of railway networks: a worldwide survey. Transp Res Part A 77:202–212
45. Ru W, Tan JX, Wang X, Wang DJ, Cai X (2008) Geographic coarse graining analysis of the railway network of China. Physica A 387:5639–5646
46. Albert R, Jeong H, Barabasi AL (2000) Error and attack tolerance of complex networks. Nature 406:378–382
47. Costa LF (2004) The hierarchical backbone of complex networks. Phys Rev Lett 93:098702
48. Zheng SQ, Kahn ME (2013) China’s bullet trains facilitate the People’s Republic of China 2016 (National Development and ReformCommission of China)
49. The 13rd Five-Year Plan for economic and social development of the People’s Republic of China 2016 (National Development and ReformCommission of China)
50. NBSC (Nation Bureau of Statistics of China) (2011). http://www.stats.gov.cn/tjzc/ztdh/sjtp/dejyjkfr/tjkr/201106/20110613_71947.htm