

Complex network analysis of China's integrated air-high-speed rail network: Topological characteristics, centrality measures, and cluster analysis

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ABSTRACT

This paper presents a comprehensive complex network analysis of China's integrated air-High-Speed Rail (HSR) network by constructing a directed weighted network and comparing its complex characteristics with its sub-networks. The findings reveal that, beyond small-world properties, the networks exhibit broad-scale characteristics with a rapid decline in degree distribution, deviating from the traditional scale-free model due to operational constraints and market saturation. Centrality analysis highlights the rising importance of secondary hubs, such as Xi'an, Kunming, and Zhengzhou, as strategic transit points linking urban centres and peripheral regions. The integrated network achieves enhanced efficiency through hybrid modularity, combining the aviation network's centralised structure with the HSR network's corridor-focused design. While this integration fosters economic connectivity and regional development, resilience challenges emerge due to reliance on high-centrality nodes. These findings offer implications for intermodal transport planning and regional development.

1. Introduction

Air-HSR intermodal transport is the strategic integration of air and HSR systems, utilising the strengths of both modes to provide a seamless, efficient and cost-effective transport solution for passengers and goods (Yang et al., 2023). This mode of transport takes full advantage of the speed of air transport and suitability for long-distance and high-value transshipments, while also utilising the extensive coverage and high carrying capacity of HSR, particularly on short- and medium-distance routes (Qi and Kwon, 2021; Sun et al., 2017). Through the implementation of air-HSR intermodal transport, passengers can enjoy convenient and smooth transfer between airports and railway stations, which greatly saves time and cost. This model not only improves the market coverage and customer retention of both airlines and railways, but also eases the fierce competition between the two modes of transport and facilitates the transition from competition to cooperation (Qi and Kwon, 2021).

In recent years, China has made great strides in promoting air-HSR intermodal transport (Yang et al., 2023). As of February 2024, the 12,306 air-HSR intermodal service has integrated the ticketing systems of major airlines, including Air China, China Eastern and China Southern

Airlines. The service now covers 78 cities and more than 2000 routes across the country, marking an important milestone in the development of intermodal transport (Beijing Release, 2024). Despite these advances in practice, there is still an urgent need to understand the underlying structural characteristics and evolutionary patterns of the air-HSR network in China. Previous studies have mainly focused on analysing the air and HSR networks separately, often ignoring the complex intermodal connections and their impact on network topology and regional connectivity (Qi and Kwon, 2021).

This paper aims to fill this gap by providing a comprehensive analysis of China's air-HSR network through complex network theory. The study will examine the structure of sub-networks and the integrated air-HSR network to ensure consistency in data processing and analysis methods. By making a detailed comparison of the topological features of the integrated and sub-networks within the same temporal and spatial dimensions, the study aims to identify the latest topological features and trends. Areas of focus include network topological features, evolutionary patterns, centrality measures and cluster analysis.

In addition, this paper investigates the truncation phenomenon observed in previous scale-free network analyses (Guimerà et al., 2005), exploring its causes as well as the new developmental patterns and

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network properties that emerge after truncation. The study will also examine the relationships and functional differences between the integrated network and sub-networks as well as between different sub-networks. By identifying regional and topological clusters within the air-HSR network and the respective strengths of major cities and inter-modal hubs, this study provides policy recommendations for future infrastructure development and network optimisation. Ultimately, this study aims to deepen the understanding of China's air-HSR intermodal network, providing insights into improving its connectivity, efficiency and resilience.

2. Literature review

2.1. Complex network analysis and topological structure of air transport networks

Complex network analysis has become an important tool for understanding the complex structure and dynamics of air transport networks. These networks, in which nodes represent airports and edges represent direct flight connections, exhibit a range of complex behaviours that can be analysed using a variety of network metrics. The application of complex network theory to air transport systems has provided important insights into their efficiency, robustness and vulnerability (Bagler, 2008; Guimerà et al., 2005; Xu and Harriss, 2008; Wang et al., 2011).

Guimerà et al. (2005) conducted a pioneering study of the global air transport network and found that the network has small-world and scale-free properties. The study highlighted the network's high clustering coefficients and short average path lengths, which suggest a small-world structure. However, the authors also observed anomalies in the centrality metrics, which were attributed to the multi-community structure of the network. Despite the seminal nature of the study, they focused mainly on static network analysis and did not consider the dynamic evolution of the network over time. Furthermore, the study's categorisation of the global air network as a scale-free network is somewhat paradoxical, as there are a number of anomalies that indicate deviations from a purely scale-free structure.

Xu and Harriss (2008) explored the network structure and node centrality of the Chinese air transport network, revealing an exponential rather than scale-free distribution. This finding suggests that the Chinese air network is more homogeneous and has fewer dominant hubs than global or other national networks. The study also highlights the importance of betweenness centrality in identifying key transport hubs within a network. The study provides valuable findings from the Chinese aviation network, but does not consider the potential impact of rapid infrastructure development on network evolution. Furthermore, while the authors correctly identify the exponential distribution of the network, they do not fully explore the implications of this finding for network resilience and scalability.

Lordan et al.'s (2014) study of the European air transport network found a double Pareto's law distribution, suggesting a more complex network structure, which may be due to the integration of multiple national networks within the EU. The double Pareto distribution identified suggests a more specific understanding of the network's topological properties. However, this study could be improved from a more detailed examination of how policies and regulations within the EU affect the development of networks. Furthermore, the impact of the double Pareto distribution on network robustness and efficiency has not been fully explored.

Several other studies have examined changes in air transport networks over time, focusing on how changes in infrastructure, policy and demand affect network topology. Jimenez et al. (2012) used network analysis to examine the evolution of Portugal's three main airports from 2001 to 2010, focusing on the impact of deregulation and the rise of low-cost carriers (LCCs). The study reveals that LCCs have significantly increased passenger numbers, while also challenging traditional airlines. Wang et al. (2011) analysed the evolving structure of the U.S. air

transport network from 1990 to 2010, and found that the degree distribution of the network evolved from an unscaled scale to a truncated power law, and that this truncation indicated a change in the network structure. The study used a longitudinal approach to gain insight into the evolution of the air network over time. However, this study failed to address the broader implications of truncated power law distributions. Despite evidence of truncation, suggesting that the network deviates from scale-free characteristics, the authors describe the network as scale-free. This oversight suggests the need for a more rigorous examination of the structure of scale-free networks in evolving background.

Similarly, Bagler (2008) studied the Indian air transport network and found that it exhibits a power-law degree distribution with significant truncation points. Like many other studies, this study treats the network as scale-free despite the presence of truncation points, ignoring the fact that this bias may indicate the emergence of new network structures. This calls for a reassessment of how truncation points are interpreted in the context of scale-free networks.

In addition, Wandelt et al. (2024) provide a comprehensive review of recent advancements in air transport network research, including applying complex network theory to assess system resilience, vulnerabilities, and operational efficiency. Their work emphasised the divergence between theoretical network studies and practical air transport applications, calling for a synthesis of these approaches to bridge operational and structural perspectives. Malighetti et al. (2019) analysed air cargo networks of global integrators like DHL, FedEx, and UPS, highlighting trade-offs between efficiency, robustness, and flexibility in multi-hub network configurations. These findings are particularly relevant in understanding how centrality, transitivity, and density metrics influence network performance under evolving regulatory and market conditions.

Although significant progress has been made in understanding air transport networks, most studies have focused on comparing the topological nature of networks in different regions or analysing the time evolution of individual networks. Few studies have conducted multilevel analyses that consider different networks (e.g., air and HSR) within the same market. This gap in the literature is significant because the integration of multiple modes of transport can lead to complex interactions that affect overall network efficiency and resilience.

2.2. Complex network analysis and topological structure of HSR networks

In contrast to the extensive literature on complex network analysis of aviation networks, research on HSR networks has been more limited and focused mainly on China, especially in the years after 2011. This attention is mainly attributed to the rapid expansion of China's HSR network, which has become the largest HSR network in the world (Wang et al., 2022). As a result, many existing studies have explored the topological characteristics of HSR networks in the context of regional geographic and socio-economic factors (Zhang et al., 2020). Despite scholars' great efforts, they still lack consensus on the structural features of these networks.

The literature on HSR networks has focused on China, as evidenced by the studies by Wei et al. (2019) and Wang et al. (2022), both of which emphasise the hierarchical structure of China's HSR network. This focus is a direct reflection of China's significant expansion in HSR infrastructure over the past decade, making it fertile ground for network analysis. In addition, the temporal distribution of these studies is skewed towards recent years after 2011, reflecting the timeline of China's HSR development.

A key area of debate in the literature has been the extent to which HSR networks exhibit scale-free characteristics. Traditional scale-free networks characterised by power-law degree distributions have been the dominant paradigm in network theory. However, a study by Wei et al. (2019) argues that China's HSR network does not conform to the scale-free model, but instead exhibits a hierarchical structure with a bimodal distribution of centrality metrics. This suggests the existence of

two different types of nodes: a few highly connected hubs and many less connected peripheral stations.

On the other hand, Wang et al. (2022), in their study of the vulnerability of the HSR network in China, note that while certain hubs dominate in terms of connectivity, the network as a whole may not follow a pure scale-free distribution. Instead, they observed truncated power laws, especially at higher degrees. This truncation challenges the notion of scale-free in HSR networks and suggests that different structures may exist.

The relationship between the topology of the HSR network and regional socio-economic and geographic factors is another recurring theme in the literature. For example, Yang et al. (2018) analysed China's HSR network and found that socio-economic factors, such as urban population density and level of economic activity, significantly influence network structure. Their study shows that regions with higher economic activity tend to have more connected HSR stations, forming regional hubs that drive the overall connectivity of the network. Similarly, Jiao et al. (2020) examined how geographic factors such as urban distribution and natural barriers affect the HSR network. They found that the topology of the HSR network is strongly influenced by the geographic distribution of cities, with HSR routes usually following major urban corridors. This leads to the emergence of regional clusters within the network that are closely related to China's economic geography.

While the link between network structure and socio-economic or geographic factors is well established, most studies have focused on descriptive rather than explanatory analyses. More causal studies are needed to explore how these factors directly shape the topology of networks and how changes in these factors may affect future network development. In addition, the potential feedback loops between network development and regional economic growth is an area for further research.

2.3. Complex network analysis and topological structure of air-HSR integrated networks

The exploration of complex network topologies for air-HSR intermodal transport remains an emerging area of transport research, with limited research dedicated to this cross-cutting area compared to more mature analyses of air or rail networks. Notably, two recent studies have contributed to this area. The first study, conducted by Qi and Kwon (2021), assesses urban connectivity within China's rapidly expanding air and HSR networks. By applying centrality metrics, this study provides an assessment of the importance and robustness of cities in an integrated network, revealing hierarchical structures and strategic hubs that promote regional and national connectivity. However, while centrality is an important aspect of network analysis, this study could be further strengthened by incorporating other topological features (e.g., average path length, modularity, and degree distributions) that are essential for a more comprehensive understanding of the structural integrity and resilience of networks.

Similarly, Yang et al.'s (2023) study advances the field by examining the impact of the development of air and HSR networks on urban development. The study highlights how these modes of transport shape urban networks, particularly from the perspective of urban hierarchy and connectivity, and explores the role played by regional geography, transport topology and socio-economic factors that drive network development. The study provides an in-depth analysis of the respective contributions of air and HSR networks to urban growth. However, the study mainly examines these networks in isolation and does not fully explore the intermodal linkages between aviation and HSR, especially how their integration affects the overall topology of urban networks.

Previous research has largely examined air and HSR networks in isolation, focusing on their individual topological characteristics, connectivity patterns, and operational efficiencies. Studies on aviation networks (e.g., Guimerà et al., 2005; Xu and Harriss, 2008) and HSR

networks (e.g., Wang et al., 2022) have provided valuable insights into their structural properties but have not sufficiently explored their intermodal interactions. The integration of air and HSR networks introduces new complexities that single-network analyses fail to capture, particularly in terms of connectivity, resilience, and efficiency trade-offs.

Despite advances in complex network research, the study of air-HSR integrated networks remains a relatively new perspective. Compared with a single network, one of the difficulties in the study of composite networks is how to unify and envelope each single network formed by different modes of transport into a whole system. Moreover, single network research is mostly based on empirical studies of the network topological characteristics, as well as network connectivity, reliability and robustness; whereas intermodal network research, in addition to the above, should also consider some of the issues specific to the integrated network, such as the relationship and the function comparison between integrated network and sub-networks.

3. Network topology characteristics

3.1. Typical network structures

The network structure of air-HSR intermodal transport networks can exhibit a variety of complex topologies, reflecting the unique characteristics and interactions between the two modes of transport. One common structure observed in such networks is the small-world network, which is characterised by high clustering and short average path lengths, enabling efficient connectivity across the network while maintaining a degree of local cohesion (Watts and Strogatz, 1998). Another frequently discussed topology is the scale-free network, where the degree distribution follows a power-law, indicating the presence of a few highly connected hubs that dominate the network's connectivity, a structure often found in both air and rail networks independently (Barabási and Albert, 1999). However, not all networks adhere strictly to the scale-free model. Some exhibit a single-scale structure, where the degree distribution is more uniform, lacking the extreme hubs seen in scale-free networks (Amaral et al., 2000). Alternatively, a broad-scale network displays a degree distribution that follows a power-law only up to a certain point, beyond which a cutoff occurs (Amaral et al., 2000).

In addition to these, hierarchical network structures can emerge, especially in large-scale networks like China's air-HSR system, where nodes are organised in a way that reflects a clear hierarchical order, often based on the importance or size of cities (Ravasz and Barabási, 2003). Such networks often show a combination of high clustering within hierarchical levels and scale-free properties across the network. Moreover, modular networks are also possible in air-HSR systems, where the network is divided into distinct modules or communities, each with dense internal connections and sparser connections between modules. This modularity can reflect regional communities within the network, where cities within the same geographic or economic region are more closely connected to each other than to cities outside the region (Newman, 2006).

3.2. Selection of network topology metrics

In this paper, the topological analyses of the air and HSR networks are to simulate the intermodal network in reality as much as possible, focusing on both the connections between nodes and the direction of paths, as well as considering the weights such as the frequency and number of trains or flights. Most studies have relied on undirected or unweighted models, which fail to capture the directionality or service frequency of transport connections. Unlike these previous studies, this paper constructs a directed weighted network for analysing the air-HSR integrated network and its sub-networks. In a directed network, each connection between stations reflects the specific direction of flight and train services, which is crucial for capturing the flow of passengers and

the network's structural behaviour. For the HSR sub-network, this approach allows for a more refined understanding of each station's role, not merely as a point along a route but as a critical node with distinct inbound and outbound connections. This perspective reveals sub-networks emanating from or converging at each station, providing a clearer picture of the network's hierarchy and the strategic importance of certain routes. Therefore, the network to be constructed is a directed weighted network. In the study of complex networks, several key metrics are employed to characterise the structure and dynamics of the networks.

Nodes: In networks, nodes (also known as vertices) denote individual entities or points connected by edges (Newman, 2011). In this paper, cities are used as nodes, as the main focus of this paper is to examine the accessibility between cities and the topological characteristics of the overall network, in order to investigate how travellers choose to travel to reach a certain destination city, rather than the accessibility between HSR stations or airports. Moreover, there is no route connection between different airports within the same city, and although there are different stops of HSR stations in the same city (e.g., Tianjin Station, Tianjin South Station), these stops are all for collecting passengers in the same city or bringing them to this city, only to give more choices to passengers in the larger cities. Therefore, if a city has both HSR stations and airports, or if a city has more than one airport or HSR station, the city itself is considered as a node.

Edges: Edges (or links) are connections between nodes. These edges represent relationships or interactions between nodes. The number of edges is the total number of direct connections between nodes in a network. Edges can be either undirected (if the connection is bidirectional) or directed (if the connection has a specific direction) (Newman, 2011). In the network of this paper, the HSR sub-network takes the city where the station is located as a node, and there is a connection between any two cities as long as the same HSR train stops at these two stations. Similarly, the air sub-network takes the city where the airport is located as the node, and there is a connection between any two cities as long as there is a flight between these two nodes. As a directed network, the edges from city A to city B, and from city B to city A, are set up as two separate directional connections.

Average Degree: The degree of a node is the number of edges connected to that node. The average degree is a measure of the average number of connections to each node in the network (Barabási and Albert, 1999). The average degree is calculated by adding the degrees of all nodes and dividing by the total number of nodes.

Average Weighted Degree: In a weighted network, each edge has a weight that indicates the strength or capacity of the connection. The weighted degree of a node is the sum of the weights of the edges connected to that node (Barrat et al., 2004). The average weighted degree is calculated by adding the weighted degrees of all nodes and dividing by the number of nodes. In this paper, the frequency of HSR and the number of flights are considered separately in the sub-networks. In the integrated network, from city A to city B if there are both flights and HSR, the frequencies are summed up as the directed weighting of the integrated network.

Network Diameter: The network diameter is the longest shortest path between any two nodes in a network (Watts and Strogatz, 1998). This metric can be used to measure the size of a network based on the maximum distance between nodes. The network diameter is calculated by determining the shortest paths between all pairs of nodes and determining the maximum length in those paths.

Modularity: Modularity is a measure of the extent of a network divided into modules (or communities) (Newman, 2006). Networks with high modularity have dense connections between nodes within modules, but sparse connections between nodes within different modules. It is often used to detect community structure within a network, with a high degree of modularity indicating a strong community structure.

Average Clustering Coefficient: The clustering coefficient of a node measures the degree of connectivity between that node's neighbours,

depicting the general tendency of nodes to cluster together in a network (Watts and Strogatz, 1998). The average clustering coefficient is calculated by averaging the clustering coefficients of all nodes. The clustering coefficient of a single node is the ratio of the number of connections between its neighbours to the maximum possible number of connections between them.

Average Path Length: Average path length is the average number of steps along the shortest path for all possible node pairs in the network (Fronczak et al., 2004). It is calculated by adding the shortest path lengths between all node pairs and dividing by the number of such node pairs. It reflects the efficiency of flow in a network.

Network efficiency refers to the ability to provide fast, reliable connectivity across the network, while resilience describes the system's capacity to maintain functionality under disruptions or failures. Both attributes are critical for understanding the performance and robustness of transportation networks, particularly in the integrated air-HSR context. To evaluate network efficiency, four key indicators are employed: (1) Average Path Length, which reflects network overall connectivity efficiency; (2) Average Clustering Coefficient, capturing the density of local connections; (3) Degree Centrality, which highlights the most connected nodes; and (4) Betweenness Centrality, which identifies nodes that facilitate shortest-path flows. For resilience, two key indicators are employed: (1) Modularity, to assess the network's ability to compartmentalise disruptions, and (2) Node Centrality, as high-centrality nodes are more critical for network robustness and more sensitive to attacks.

Although the above indicators measure the air network, the HSR network and the integrated network in the same dimension, the integration of air and HSR networks presents inherent challenges due to the fundamental differences in their operational characteristics. While this study constructs a directed weighted network to represent connectivity through edges and service density through weights, it is important to acknowledge that the connectivity edges in the air network are not directly equivalent to those in the HSR network. Aviation connections are driven by market demand and operational decisions, allowing for flexible, independent links between nodes, whereas HSR connections are geographically constrained, determined by the physical adjacency of stations along track corridors. These structural disparities introduce complexities in integrating the two networks into an integrated framework.

Additionally, operational metrics such as speed, price, and volume for air and HSR routes could not be directly combined with service frequency to form a composite connectivity metric due to their distinct natures. Speed reflects travel time, price influences cost efficiency, and volume captures passenger capacity. Incorporating all these dimensions into a unified network would require weighting and normalisation schemes that could introduce inconsistencies or biases. Consequently, service frequency was chosen as the primary weighting factor to construct the integrated network, as it provides a straightforward representation of service delivery intensity.

Moreover, while this study employs a topological analysis framework to explore the spatial structure of China's integrated air-HSR network, the methodology inherently focuses on spatial connectivity rather than temporal or operational dimensions. The connectivity measures used, such as the number of flights or train services between cities, reflect the network's structural properties but do not account for the degree of schedule synchronisation or operational alignment between air and HSR services. The absence of such synchronisation, as observed in schedule data for example cities like Beijing, Chengdu, Zhengzhou, and Guiyang, highlights the current limitations of inter-modal integration in practice.

3.3. Data collection

The study area is limited to mainland China, there are 187 cities with airports and 252 cities with HSR stations. Since mainland China did not

fully reopen its borders until March 2023, following the lifting of Covid-related control policies. This delay had a significant impact on air and HSR traffic and scheduling, with network operations not yet fully recovered to pre-pandemic levels. As such, 2023 data would not provide a complete or representative view of the network. To ensure the analysis reflects the most realistic and stable network operations, this study uses 2019 data, representing the last full year of normal operations before the pandemic, with air network data from OAG Analyser, and HSR network data from the 12,306 China Railway (2019). According to the previous research (Jiao et al., 2017; Yang et al., 2019) and the definition released by the National Railway Administration, this paper defines HSR lines as new built railway lines with an average speed of 250 km/h or more and upgraded railway lines with an average speed of 160 km/h or more, running G, D and C trains (referred to as high-speed trains). On this basis, the schedule of HSR on 12 December 2019 was collected. For air transport, the city pairs with an average daily frequency greater than or equal to 1 flight in operation in 2019 were selected.

The network topological indicators are calculated with Gephi software (shown in Table 1), and the air-HSR integrated network consists of 328 city nodes with 6675 edges; among them, the HSR sub-network consists of 252 cities and 5210 routes; and the air sub-network consists of 187 cities and 2451 non-stop flight routes.

The average path length of the integrated network (2.19) is lower than both the air (2.38) and HSR (2.26) networks, indicating improved network connectivity and efficiency. Additionally, the integrated network exhibits the highest clustering coefficient (0.71), reflecting more cohesive network connections, which contribute to reduced transfer times and increased travel efficiency. However, the modularity of the integrated network (0.45) is slightly lower than that of the HSR network (0.496), suggesting moderate compartmentalisation. This reduction reflects increased interconnectivity between the air and HSR systems, which, while enhancing efficiency, slightly reduces localised resilience.

3.4. Air sub-network topology characteristics

There are 187 nodes and 2451 edges in the aviation sub-network consisting of all cities with airports in Mainland China. The average degree is 13.043 indicating that on average each city is directly connected to about 13 other cities. The average weighted degree is 54.021, indicating that the overall connectivity of each city is significantly higher when weighting (frequency) is considered, with an average of 4 daily flights per city to each connected city. A network diameter of 4 indicates that the longest shortest path between any two cities in the network is 4 steps, suggesting that a maximum of three transits are required to all cities in the air network. The average path length of 2.377 indicates that, on average, only slightly more than 2 steps, i.e., one stopover, are required to reach any one city from another city, indicating a high level of connectivity.

The clustering coefficient focuses on the connectivity of the network and the tendency of nodes to form tightly connected groups. The average clustering coefficient of the aviation network is 0.551, indicating on

average, about 55.1 % of the nodes' neighbours are also connected to each other, which means that if an airport is connected to two other airports, the likelihood that there is a direct flight between those two neighbouring cities is 55.1 %.

Modularity measures the overall structure and the extent of the network's division into communities or modules. A high modularity indicates dense connections within modules, but sparse connections between modules. A modularity score of 0.127 for the air network indicates a weak modular structure. This indicates that the division of groups within the aviation network is not very obvious, meaning that the network as a whole is relatively well connected and not strongly divided into separate regions or groups of cities.

From the topology diagram of the aviation sub-network in Fig. 1, each node represents a city, the node size indicates degree centrality, each edge represents direct flight routes between each city, and the colour shades of the edges indicate the weights (average daily frequencies). The colours of the nodes indicate the different communities or groups detected in the network. The blue group includes the majority of the major hub cities such as Beijing, Shanghai and Shenzhen, and the density of connections indicates strong connectivity between cities within the blue region. The lower orange group includes mainly northwestern cities such as Xi'an, Urumqi, and Yinchuan, with Xi'an being the most obvious group hub, and this group represents the formation of a regional group with high internal connectivity between these northwestern cities. There is also a red group at the top of the image with Hohhot as the core hub, which connects Inner Mongolia Autonomous Region cities such as Chifeng, Ulanhot and Hulunbeier through Hohhot, reflecting the route network characteristics of Inner Mongolia that connects to internal and external cities through regional hubs. Similarly, there is a yellow group with Kunming as the hub in the upper right of the diagram. This group is mainly connected to other provincial cities in Yunnan Province, such as Lijiang and Dali, through Kunming, the capital of Yunnan Province, as well as to some eastern cities that are closely connected to Yunnan Province, such as Zhengzhou and Quanzhou.

3.4.1. Small-world network characteristics

Analysing the structural properties of networks is crucial for understanding their efficiency, connectivity, robustness, and evolutionary patterns. As mentioned, two fundamental properties frequently examined in network science are scale-free and small-world characteristics. Scale-free networks are characterised by a power-law degree distribution, where a few hubs possess significantly more connections than the majority of nodes (Barabási and Albert, 1999). This hierarchical growth leads to networks where major hubs play pivotal roles in maintaining global connectivity. Small-world networks exhibit high clustering coefficients and short average path lengths, facilitating efficient local and global connectivity (Watts and Strogatz, 1998). These properties ensure that any two nodes can be reached through relatively few steps, enhancing the network's operational efficiency.

The degrees of all cities in the aviation sub-network were made into a degree distribution graph (Fig. 2). It can be seen that a few nodes (hubs) have a very high degree, only 20 % of nodes have a degree higher than 50 and only 10 % of nodes have a degree higher than 82, implying that they are connected to many other nodes, and these hubs play a crucial role in maintaining the connectivity and robustness of the network, while the majority of the nodes have a relatively small degree, with 80 % of nodes having a degree of less than 50, and a relative low level of connectivity.

Further plotting of the cumulative degree distribution provides a more intuitive illustration of the power-law relationship (Fig. 3). The double logarithmic plot of the cumulative degree distribution is clearly divided into two parts, with the first half showing an approximately linear relationship, and the second half of the tail distribution decaying faster than the power law decay. The first section is well suited for nodes with lower degrees, indicating power law behaviour in this range. This

Table 1
Network topological indicators.

	Air network	HSR network	Integrated network
Nodes	187	252	328
Edges	2451	5210	6675
Average Degree	13.04	19.58	29.03
Average Weighted Degree	54.02	153.52	234.96
Network Diameter	4	5	4
Modularity	0.127	0.496	0.45
Average Clustering Coefficient	0.55	0.51	0.71
Average Path Length	2.38	2.26	2.19

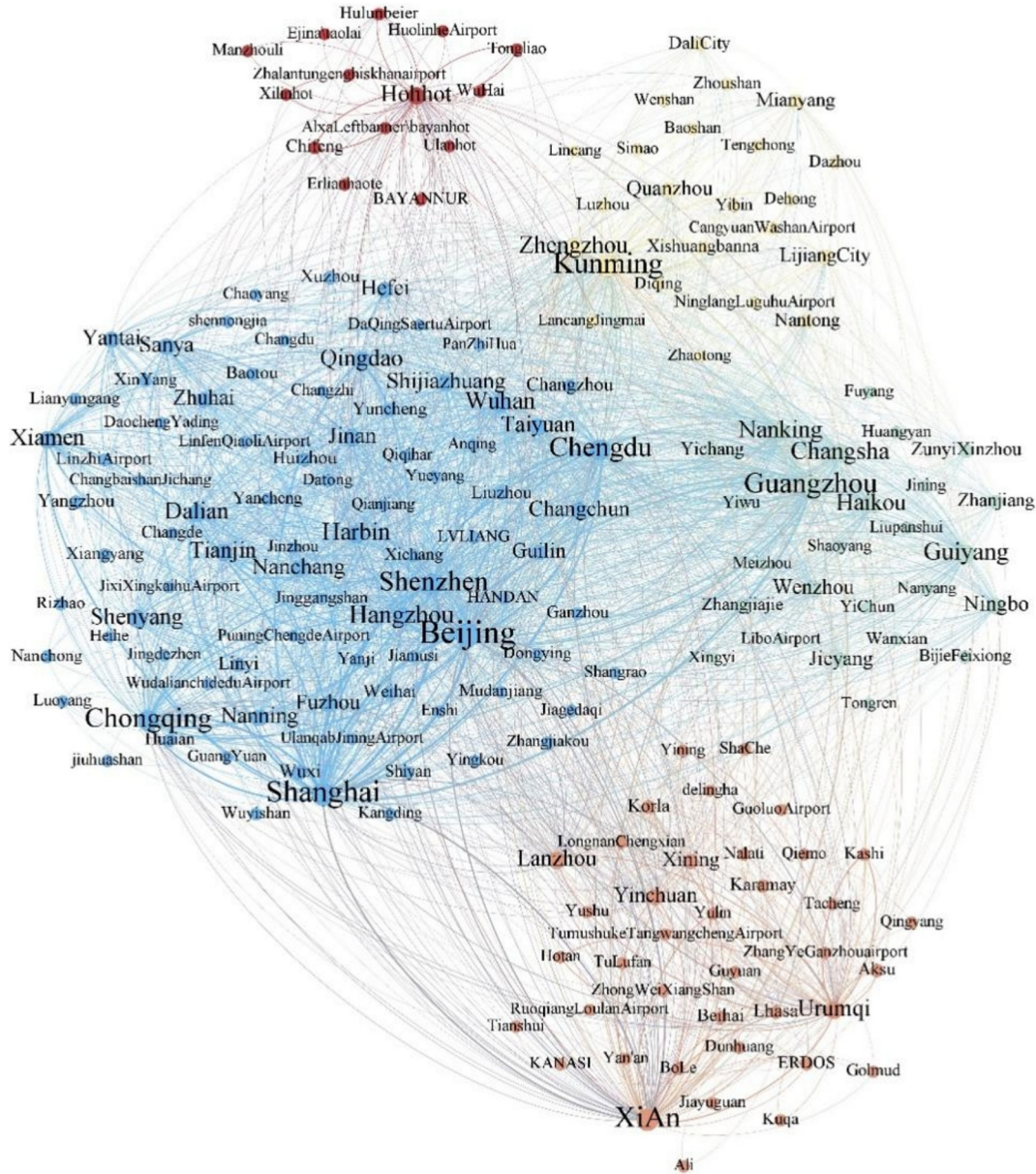


Fig. 1. Topological structure for the air sub-network.

segment indicates that nodes with fewer connections have traditional scale-free behaviour. The second, steeper segment for high-degree nodes indicates a different scaling behaviour. This can be explained by capacity constraints at city airports or saturation effects limiting the degree expansion. As shown in Fig. 4, data collected for the top 50 airports (by passenger number) in China reveals that 29 of these airports exceeded their designed passenger capacity in 2019. This overutilisation limits their ability to accommodate additional connections, resulting in a slower growth rate of the degree distribution at higher connectivity levels. Scarce capacity and saturation effects lead to a truncation in the degree distribution, deviating from the scale-free network pattern often observed in unconstrained networks. In a scale-free network, a continuous growth in connectivity would be expected, with some nodes achieving exceptionally high degrees. However, in the presence of capacity constraints and saturation, the degree distribution exhibits a cutoff or a sharp decline beyond a certain point. This truncation reflects the practical limitations of expanding connectivity in real-world networks, where infrastructure capacity impose upper bounds on growth.

After fitting, the truncation point is when the degree (K) is equal to

56 (K_c), the slope of the first linear fit is -0.497 , R^2 is 0.969; the second segment is a quadratic function with downward opening, and R^2 is 0.952. It can be seen that the fitting relationship of both segments is very good, so the degree of there air sub-network no longer conforms to the single power-law distribution, and no longer conforms to the characteristics of a scale-free network, but conforms to the broad-scale network characteristics, i.e., the degree distribution presents a power-law state at low degrees, but transforms to a fast-decaying status at higher degrees.

The degree distribution function of the air sub-network is:

$$\ln P(K) \sim \begin{cases} -0.4973 \ln K + 0.3167, & K \leq K_c \\ -2.7691 \ln^2 K + 23.186 \ln K - 50.722, & K > K_c \end{cases} \quad (3-1)$$

Among which, $K_c = 56$.

To further verify whether the air sub-network has small-world attributes, a random network with the same number of nodes, number of directed edges and average weighting as the existing aviation topology network is generated using Python and NetworkX, and the average path length and cluster coefficient of the random network are calculated. The average path length of the weighted random network is 3.713,

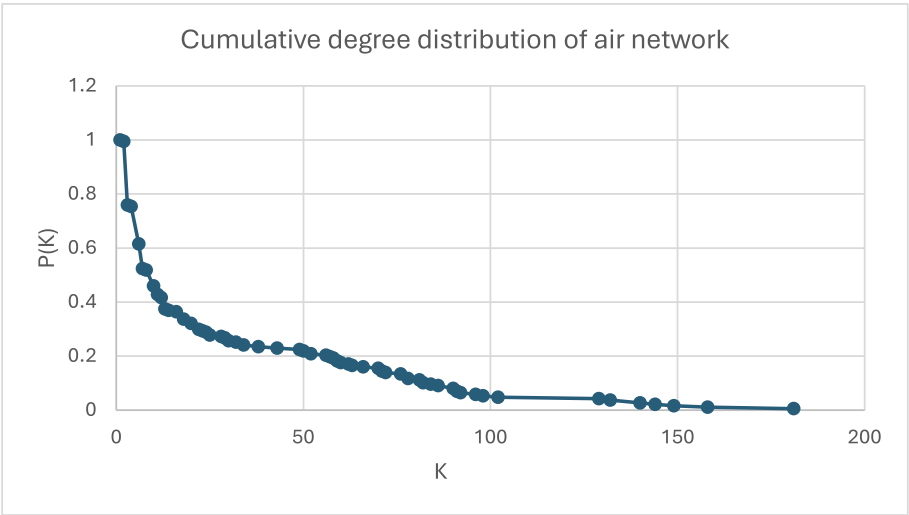


Fig. 2. Cumulative degree distribution of the air sub-network.

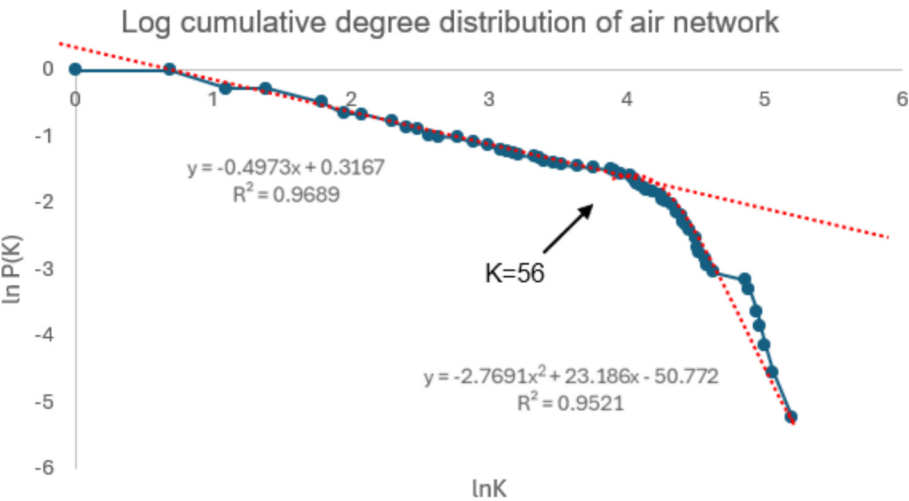


Fig. 3. Logarithm cumulative degree distribution of the air sub-network.

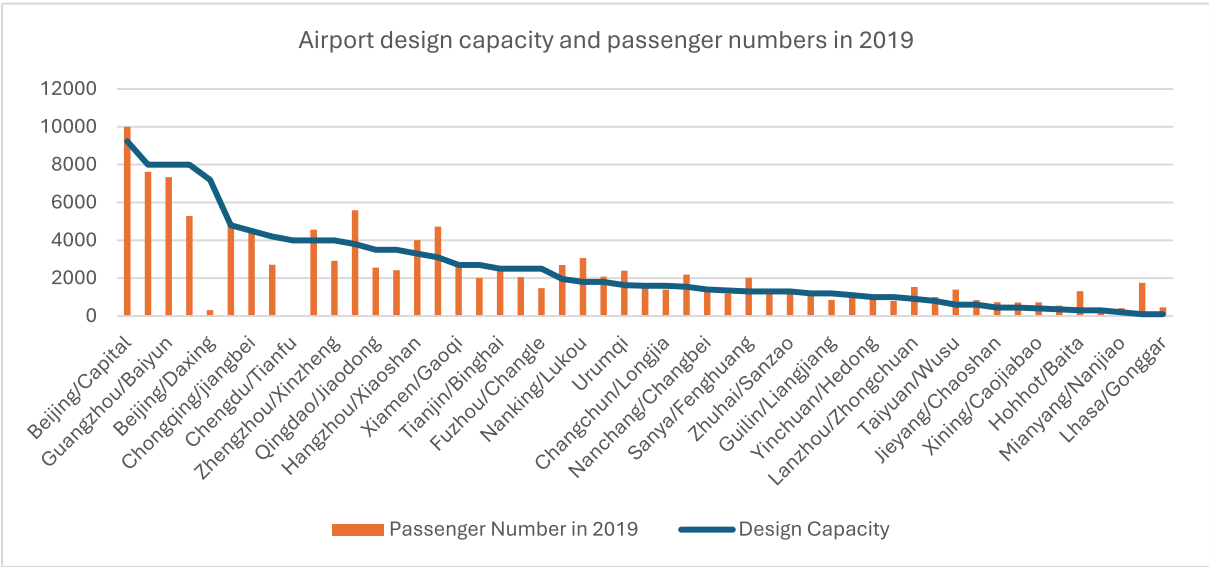


Fig. 4. Airport design capacity and passenger numbers in 2019.

indicating that the effective distance between cities increases when in a random network of the same size. The clustering coefficient is 0.060, indicating a very low tendency for nodes to cluster together in the weighted random networks. Typically, a network has small-world characteristics if it has a shorter average path length than a random network of the same size, and with a significantly higher clustering coefficient. By comparing these metrics to the actual air sub-network, it can be determined that the actual air sub-network exhibits small-world characteristics.

3.5. HSR sub-network topology characteristics

The HSR sub-network has 252 nodes and 5210 edges, which has more nodes and edges than the aviation sub-network, indicating that the

HSR network is more extensive and has many connections in Mainland China. The average degree of 19.583 indicates that each city in the HSR network is connected to 19 cities on average, which is higher than the average number of connections in the aviation network, which reflects the linear operation mode of the railways, that directly links many cities with a single line and multiple stops, whereas most of the aviation network is dominated by direct flights often without stops. The average weighted degree of HSR network is 153.516, which means that the average one-way frequency to each connected city is close to 8 trains per day, and this service density is also higher than the average 4 flights per day for air transport, which shows that the degree of city interconnection is higher on HSR routes. The diameter of the network is 5, which is slightly larger than that of the aviation network, indicating that the shortest path between the farthest cities is slightly longer, and the cities

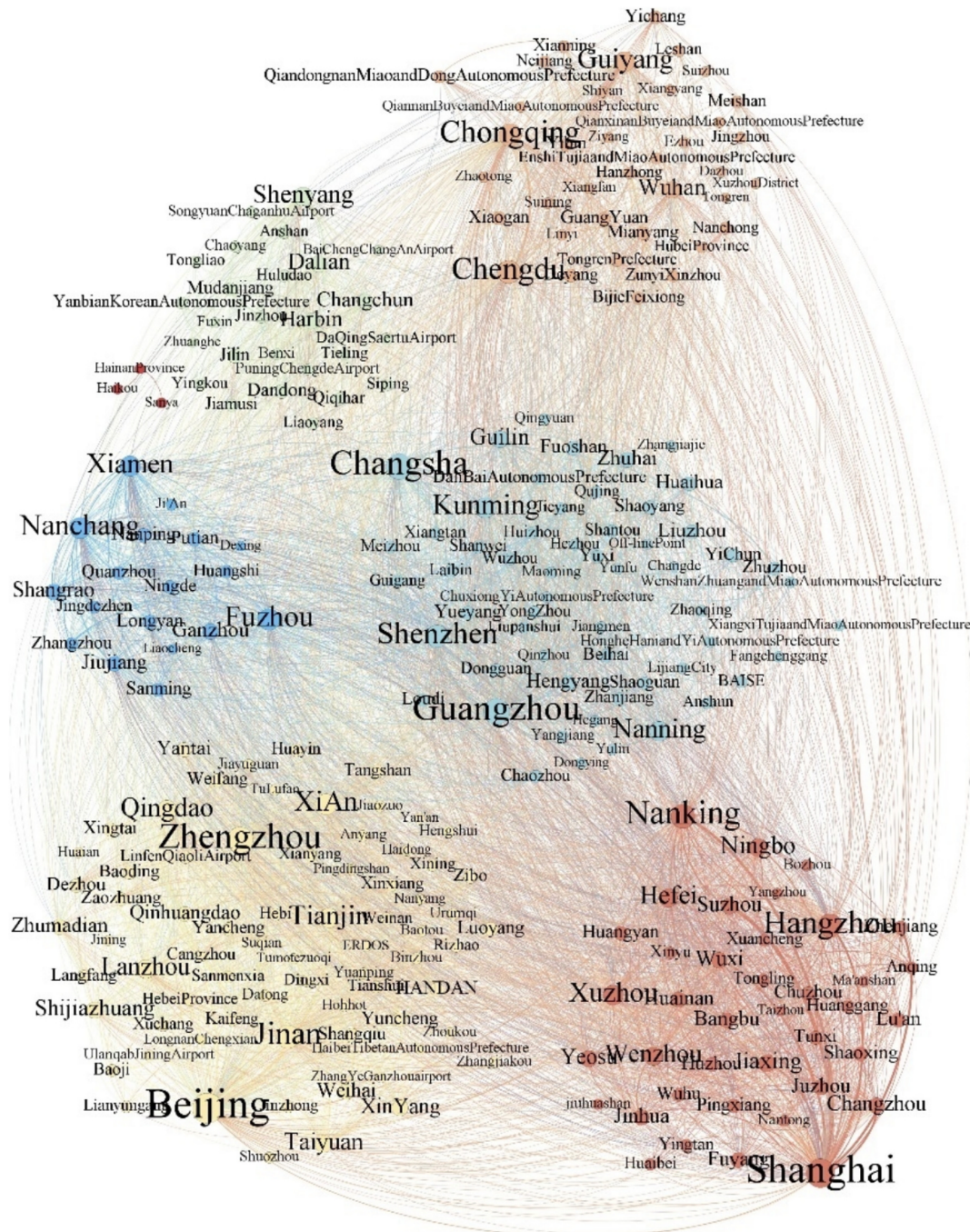


Fig. 5. HSR sub-network topology diagram.

that are further apart in the network require 4 transfers to be reached. The average path length is 2.262, which is similar to that of the aviation network, indicating that on average, it takes only slightly more than 2 steps, i.e. one transit, to reach another city from any one city via HSR.

The average clustering coefficient of the network is 0.509, which is slightly lower than the air network but still shows a good level of clustering. On average, about 50 % of the node cities have neighbours that are also connected to each other, which means that if one HSR city is connected to two other HSR cities, there is a 50 % probability that these two neighbouring cities have HSR connections. The modularity score of 0.496 indicates a stronger community structure than the air network, suggesting the existence of different communities within the HSR network.

As can be seen from the topology of the HSR network in Fig. 5, China's HSR network is clearly divided into six groups, which are mainly concentrated among the cities connected along the HSR lines. Each group basically represents a different geographical region (see Fig. 6), which are North China group, East China group, South China group, Southeast group, Northeast group and Southwest group, and the cities in the groups are mostly connected by the same HSR line. The North China group with Beijing and Zhengzhou as the core hubs contains regional

hub cities such as Jinan, Tianjin and Qingdao, as well as some closely connected Northwest China hub cities such as Xi'an and Lanzhou (due to faster HSR construction in the East, many HSR in Northwest China have not yet been completed or have few operations as of 2019, and thus do not form a separate regional group). The East China group, centred on Shanghai, Hangzhou, and Nanjing, contains regional hubs such as Xuzhou, Ningbo, and Hefei. The cities within this group are all in the Yangtze River Delta region, and the dense network around them suggests a high degree of regional connection, which has fostered rapid economic activity and regional development. Similarly, the South China group, with Guangzhou and Shenzhen at its core, contains the major cities in the Pearl River Delta region, as well as connecting regional hubs such as Changsha, Kunming and Nanning, radiating to the neighbouring provinces, demonstrating the strong driving potential of the region and the vast hinterland. The three smaller groups are the Southwest group centred on Chongqing and Chengdu, the Northeast group centred on Shenyang, and the Southeast group centred on Xiamen, Nanchang and Fuzhou. Although they cover a relatively small area, they still show a strong connectivity and regional integration level with the neighbouring cities, indicating a well-developed local economy and strong transport links, reflecting the important role of the HSR line as an economic



Fig. 6. HSR route map of China (Source: ChinaMap360).

corridor.

3.5.1. Small-world network characteristics

Similar to the aviation sub-network, the degree of all cities in the HSR sub-network is plotted into a degree distribution graph (Fig. 7). It can be seen that a few nodes have very high degrees, with only 20 % of the nodes having a number of connections higher than 56 and only 10 % of the nodes having a number of connections higher than 100; whereas the majority of the nodes have a relatively small number of connections and low connectivity.

Further plotting of the logarithm cumulative degree distribution shows that the logarithmic graph of the HSR sub-network is also divided into two parts, with the first half showing an approximately linear relationship, indicating that nodes with fewer connections have a traditional scale-free behaviour (see Fig. 8). The second half of the distribution decays more rapidly than the power law. For the HSR network, passenger data for individual train or station is not available, preventing a direct analysis of capacity constraints. However, the structural properties of HSR networks inherently limit connectivity. The faster-than-power-law decay in the degree distribution is likely due to the physical constraints of rail lines, where a city's location along a specific track determines the maximum number of cities it can connect to directly.

After fitting, the truncation point is when the degree is equal to 24, the slope of the first linear fit is -0.2458 , and the R^2 is 0.8682; the second is a quadratic function with downward opening, and the R^2 is 0.9782. Thus, it can be seen that the two fitting relationships are very high, so the degree of the HSR sub-network is no longer in line with the characteristics of a single power-law distribution, and no longer conforms to the characteristics of the scale-free network, but conforms to the characteristics of the broad-scale network characteristics. Overall, the degree distribution presents a power-law state at low degrees, but transforms into a fast-decaying status at higher degrees.

The degree distribution function of the HSR sub-network is:

$$\ln P(K) \sim \begin{cases} -0.2458 \ln K + 0.3045, K \leq K_c \\ -0.6398 \ln^2 K + 3.8152 \ln K - 6.473, K > K_c \end{cases} \quad (3-2)$$

Among which, $K_c = 24$

Similarly, to further verify whether the HSR sub-network has the small-world property, a random network with the same number of nodes, number of directed edges, and average weighting degree as the existing HSR topological network is generated using Python and NetworkX. It is computed that the random network has a larger average path length (3.33) and a lower aggregation factor (0.148) than the

current HSR sub-network. Therefore, it can be determined that the HSR sub-network also has small-world properties.

3.6. Air-HSR integrated network topology characteristics

As shown in Table 1, the integrated network combines the nodes and edges of the aviation and HSR networks, with 328 nodes and 6675 edges, with the highest average and weighted degrees, indicating that the intermodal network has substantially more direct connectivity and service density than the individual sub-networks, meaning that the integrated network is highly interconnected. The average clustering coefficient is 0.714, the highest among the three networks, indicating a strong clustering ability and the formation of highly interconnected groups, with a high probability of 71.4 % that neighbouring nodes are connected to each other. The modularity score of 0.45 is slightly lower than that of the HSR network, indicating that the integrated network contains new solid communities, which form new groups compared to the individual aviation and HSR sub-networks, reflecting new regional geographic characteristics or functional groupings of the nodes. The average path length of 2.191 is the shortest among the three networks, highlighting the efficiency gains brought about by the integration of the networks, making travelling across the transport system faster.

The integrated network demonstrates improved efficiency, with the highest average degree and shortest average path length. This highlights the benefits of the integration of the air and HSR networks. The integrated network also has the highest average clustering coefficient, reflecting the strong overall connectivity achieved by the combination of air and HSR nodes. Meanwhile, the integration also enhances the resilience and redundancy of the national network.

As can be seen from Fig. 9, the intermodal network has integrated the characteristics and connectivity of the sub-networks, regenerating four larger groups and two smaller groups. Many cities with prominent positions in the aviation network and those with advantageous positions in the HSR network have been synthesised in the intermodal network. The intermodal network is characterised by both the air network, which divides groups by hub cities, and the HSR network, which divides groups by geographical regions. Beijing, Tianjin, Qingdao and Jinan together lead the yellow group, which includes cities in North China, Northeast China and Inner Mongolia that are closely linked to these regions. Xi'an, Chengdu, Chongqing and Zhengzhou together lead the brown group, which includes most of the cities in the western and central regions. This group also includes many less connected western cities, making it the densest group.

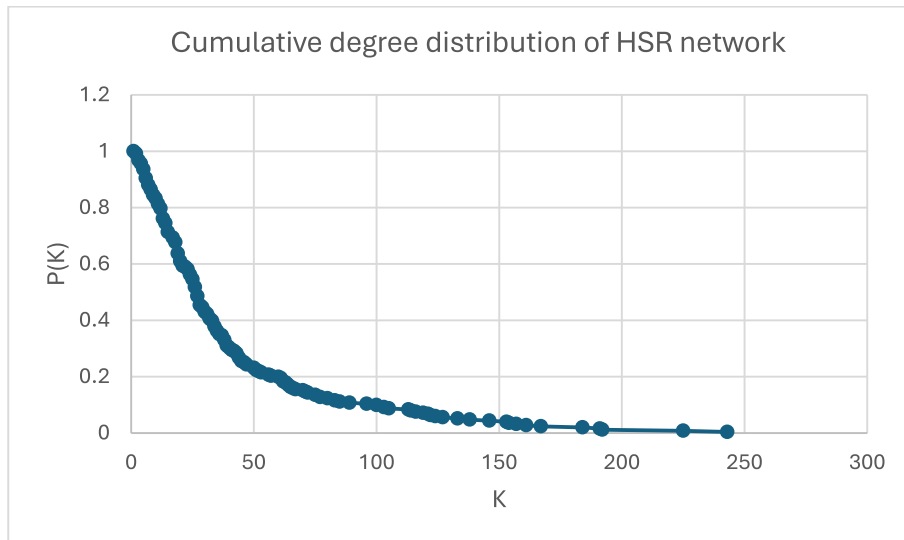


Fig. 7. Cumulative degree distribution of HSR network.

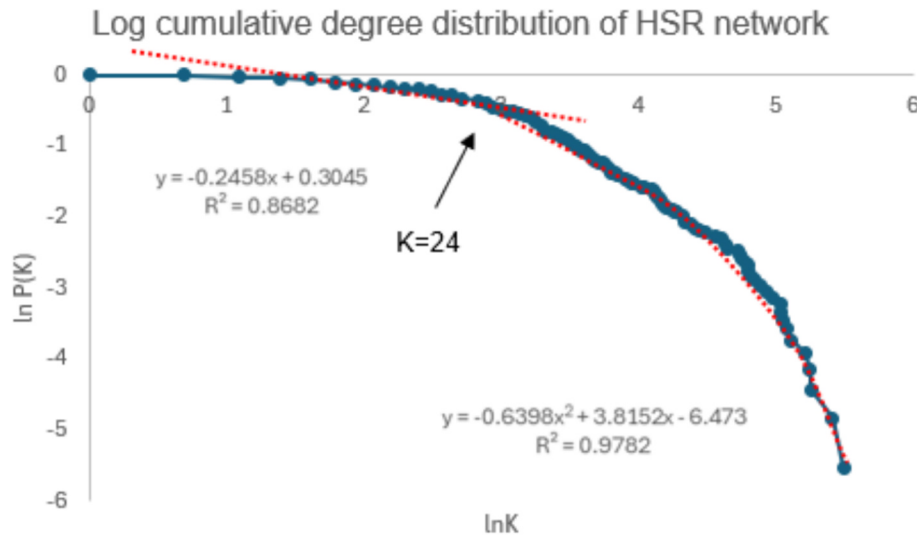


Fig. 8. Logarithm cumulative degree distribution of HSR network.

Guangzhou, Shenzhen, Changsha, Kunming and Guiyang together lead the light blue city group of the central-south and south-western regions. This group has the largest number of hub cities with large nodes, mainly the southern provincial capitals, which are well-balanced in terms of aviation and HSR, driving the development of the neighbouring regions. The bottom red group, led by Shanghai, Nanjing and Hangzhou, mainly includes cities in the Yangtze River Delta region. Although the number of cities in this group is small, the nodes of each city are larger, indicating that aviation and HSR are well-developed in all cities in this region, and that each city has strong external connectivity. The other two smaller groups are the intra-Hubei group, led by Wuhan, and the Fujian-Jiangxi groups, led by Nanchang, Fuzhou, and Xiamen. The fact that these two regions has formed smaller individual groups suggests that these provinces have a high degree of HSR connectivity, with very well-developed inter-city HSR connectivity within the province and between the neighbour provinces. Its connectivity is so dense that it will not be dissolved even if it is placed in the air-HSR intermodal network.

3.6.1. Small-world network characteristics

Similarly, a degree distribution graph is made of the degrees of all cities in the intermodal network (Fig. 10). Similar to the two sub-networks, a few nodes have very high degrees, while most nodes have a relatively small number of connections, with a limited number of cities directly connected. Further plotting of the logarithmic cumulative degree distribution shows that the logarithmic graph of the intermodal network is similarly split into two parts, with the first half showing an approximately linear relationship, indicating that the less connected nodes have a traditional scale-free behaviour, i.e., the connectivity of the nodes grows rapidly before the turning point and new nodes are preferentially linked to nodes with a higher degree of connectivity (See Fig. 11). The second half of the distribution decays faster than the power law, which further illustrates the combined effects of the constraints. Cities with combined connectivity below 56 account for 83 % of the total, indicating that most cities are directly connected to no more than 56 other cities in the intermodal network. Beyond this threshold, the growth rate of connectivity slows significantly. This suggests that, in addition to capacity constraints, market saturation effects come into play. Many cities likely reach a point where connecting to approximately 50 cities sufficiently meets local travel and economic demands, leading to gradual saturation in connectivity growth.

The fitting analysis revealed that the truncation point occurs at a degree of 34. The slope of the first linear fit is -0.4084 , with an R^2 value of 0.8935 , while the second fit follows a downward quadratic function

with an R^2 value of 0.9819 . These results indicate a strong correlation in both fits, suggesting that the intermodal network does not conform to the characteristics of a single scale-free network. Instead, it aligns with the properties of a broad-scale network, where the degree distribution follows a power-law pattern at lower degrees but transits to a rapidly decaying state at higher degrees.

The degree distribution function of the air-HSR intermodal network is:

$$\ln P(K) \sim \begin{cases} -0.4084 \ln K + 0.4988, & K \leq K_c \\ -0.8923 \ln^2 K + 6.0688 \ln K - 11.636, & K > K_c \end{cases} \quad (3-3)$$

Among which, $K_c = 34$

As before, the same process using a random network was followed to verify whether the intermodal network exhibits small-world properties. The analysis revealed that the average path length (3.37) of the random network was greater, while its clustering coefficient (0.121) was significantly lower compared to the intermodal network. These findings confirm that the intermodal network indeed possesses small-world characteristics.

A comparison of the degree distributions across the three networks reveals distinct growth patterns. The aviation sub-network shows the fastest growth when the degree of connectivity is less than 20 , with the cumulative degree distribution reaching 0.7 . This indicates that 70% of the cities have direct aviation connections to fewer than 20 other cities. Cities with connectivity degrees between 20 and 56 represent 10% of the total, and the growth of the degree distribution in this range slows, suggesting that only a few small and medium-sized cities have air connectivity in this range. The connectivity range of 56 to 102 accounts for 16% of the cities, where the degree distribution is relatively even, indicating that most large cities have a balanced distribution of air connectivity within this range. There are eight megacities with connectivity degrees exceeding 102 , representing just 4% of the total. These cities—Beijing, Shanghai, Xi'an, Kunming, Guangzhou, Chengdu, Chongqing, and Shenzhen—exhibit smooth and even degree distributions, with Beijing having the highest connectivity degree at 181 domestic cities.

The HSR sub-network, on the other hand, exhibits rapid and even growth in city connectivity when the degree is below 50 , with these cities predominantly located along a single HSR line, accounting for 78% of all cities. The growth rate significantly decreases once connectivity exceeds 50 , with only 22% of cities located at the intersections of two or more HSR lines, benefiting from increased connectivity opportunities. Among these, six cities—Beijing, Shanghai, Guangzhou, Zhengzhou,

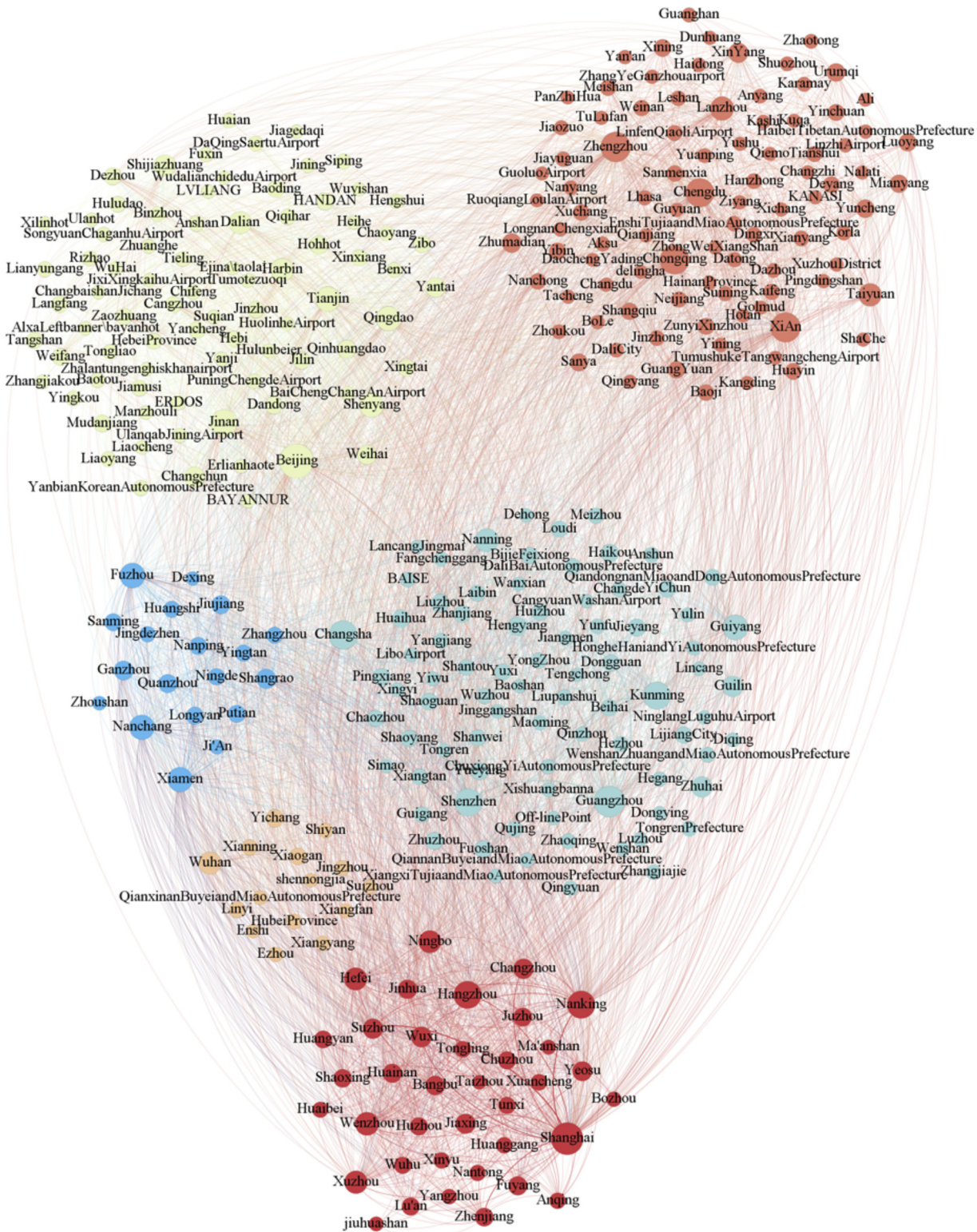


Fig. 9. Topology diagram of the air-HSR integrated network.

Changsha, and Nanjing—are major hubs with more than 160 HSR-connected cities.

The intermodal network combines features from both the air and HSR sub-networks, showing faster growth when city connectivity is less than 56, followed by a gradual slowdown. Cities with combined connectivity below 56 account for 83 % of the total, indicating that most cities are directly connected to no more than 56 other cities in the

intermodal network. The growth rate slows further as connectivity exceeds 56, with sporadic breakpoints appearing at the tail end. The super-connected cities in the intermodal network mirror those in the HSR sub-network—Beijing, Shanghai, Guangzhou, Zhengzhou, Changsha, and Nanjing—suggesting that the HSR network plays a crucial role in enhancing regional connectivity when air connectivity is already high in major hub cities.

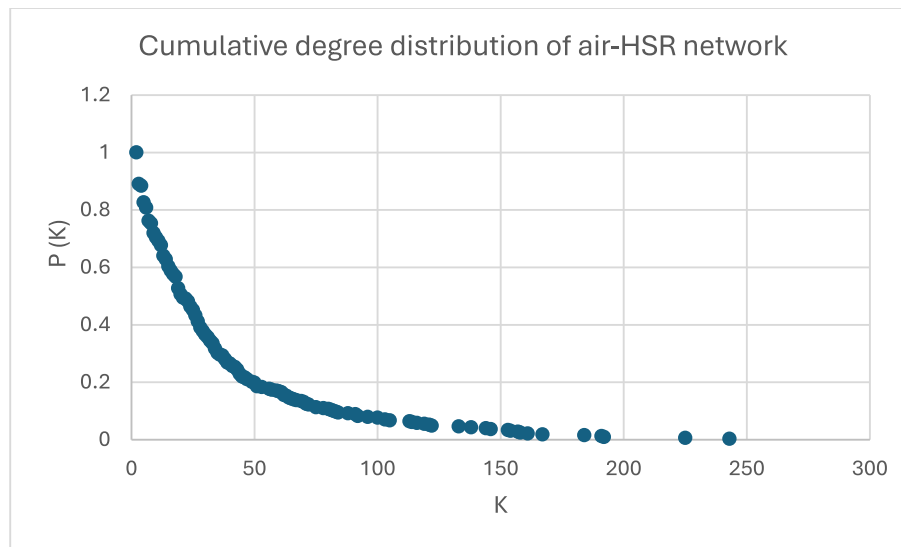


Fig. 10. Cumulative degree distribution of the air-HSR network.

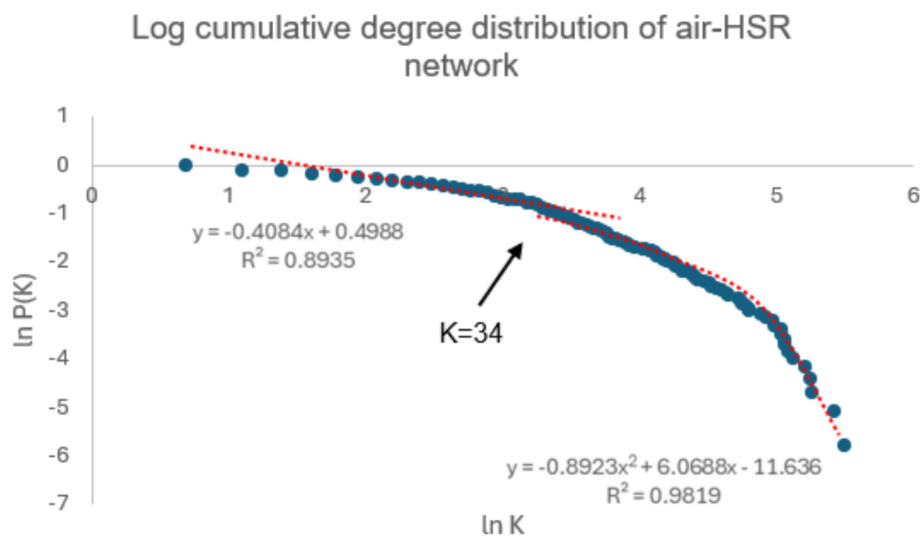


Fig. 11. Logarithm cumulative degree distribution of air-HSR network.

4. Measurement of centrality in networks

Building on the foundational concept of Social Network Analysis (SNA), centrality is a key metric used to assess the relative importance of nodes within a graph (Landherr et al., 2010). In the context of network analysis, several centrality metrics are commonly employed, including degree centrality, betweenness centrality, and closeness centrality (Freeman et al., 1991). Degree centrality measures the extent of a node's connections, while betweenness centrality reflects the likelihood of a node acting as a mediator within the network. Closeness centrality, on the other hand, indicates the relative reachability of nodes within the network (Cohen et al., 2014). Additionally, metrics such as eigenvector centrality and PageRank have been used to capture the influence of nodes that are well-connected to other influential nodes (Wang and Cullinane, 2016).

Despite the widespread use of these metrics, the concept of centrality is interpreted in various ways by different scholars, leading to diverse classifications and definitions. Although there is no universally agreed-upon definition of 'centrality', the existing literature generally converges on similar interpretations, providing a quantitative approach to measuring the relative importance of network elements. Previous

studies on network centrality and clustering have primarily focused on single-mode transport systems, limiting the understanding of how intermodal connectivity influences city rankings.

In this study, five centrality indicators are selected to evaluate the importance of different cities from multiple perspectives, drawing on centrality theory in complex networks. By integrating these measures across both the air and HSR sub-networks, this study identifies how cities shift in importance within the combined network. This approach provides a comprehensive assessment of key nodes within the air-HSR intermodal transport system, offering deeper insights into the varying roles that central cities play and enabling a more nuanced ranking of hub cities.

4.1. Selection of centrality indicators

1) Degree centrality

Degree centrality is a measure used in network analysis to determine the importance or influence of a node within a network (Freeman et al., 1991). It is one of the simplest centrality measures and is calculated based on the number of direct connections a node has. Nodes with high

degree centrality are often considered important due to their numerous connections.

The degree centrality of a node is calculated as:

$$C_D(v) = \text{indeg}(v) + \text{outdeg}(v) \quad (4-1)$$

Where $\text{indeg}(v)$ is the number of incoming edges and $\text{outdeg}(v)$ is the number of outgoing edges of node v .

2) Weighted degree centrality

Weighted degree centrality is a measure used in network analysis to quantify the importance or influence of a node based on the sum of the weights of the edges connected to it (Barrat et al., 2004). Unlike the traditional degree centrality, which only counts the number of edges connected to a node, weighted degree centrality takes into account the strength or capacity of these connections. A node with a high weighted degree centrality has many strong connections, making it a potentially influential or central node within the network.

For a given node, the weighted degree centrality is calculated as:

$$C_w(v) = k(v) \times \bar{w}(v) \quad (4-2)$$

Where $k(v)$ represents the degree of the node (number of connections);

$\bar{w}(v)$ is the average weight of the edges connected to the node.

3) Betweenness centrality

Betweenness centrality is a measure used in network analysis to quantify the importance of a node (or edge) in facilitating communication or interaction between other nodes. It is based on the concept of shortest paths and reflects how often a node appears on the shortest paths between other nodes in the network (Freeman et al., 1991). Nodes with high betweenness centrality are critical for communication within the network.

For a given node, the betweenness centrality is calculated as:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (4-3)$$

Where

σ_{st} is the total number of shortest paths from node s to node t ;

$\sigma_{st}(v)$ is the number of those shortest paths that pass through node v .

The sum is taken over all pairs of nodes s and t in the network, excluding the node v itself.

4) Harmonic closeness centrality

Harmonic closeness centrality is an alternative measure of closeness centrality that is useful for dealing with disconnected or sparsely connected networks (Rochat, 2009). It measures the influence of a node in a network by considering the inverse of the shortest path distances to all other nodes, emphasising closer nodes more than distant ones. Nodes with higher values are more central within the network, having shorter average distances to all other nodes.

For a given node, the harmonic closeness centrality is calculated as:

$$C_H(v) = \sum_{u \neq v} \frac{1}{d(u, v)} \quad (4-4)$$

Where: $d(u, v)$ is the shortest path distance between nodes u and v ;

If u and v are not connected, $d(u, v)$ is considered to be infinite, and thus $\frac{1}{d(u, v)}$ is zero.

5) Eigenvector centrality

Eigenvector centrality is a measure of node influence that considers

the importance of a node's neighbours (Bonacich, 2007). Eigenvector centrality is based on the idea that a node's centrality is determined by the centrality of its neighbours. Nodes with high scores are connected to many nodes that are themselves well-connected. These nodes are often considered highly influential within the network.

For a given node, the eigenvector centrality is calculated as:

$$C_E(v) = \frac{1}{\lambda} \sum_{u \in \text{Neighbours}(v)} A_{uv} C_E(u) \quad (4-5)$$

Where: $C_E(v)$ is the eigenvector centrality of node v ; λ is a constant (the largest eigenvalue of the adjacency matrix A ; A_{uv} represents the connections between nodes u and v).

4.2. Results of centrality measurements

Using Gephi software, the centrality metrics—degree centrality, weighted degree centrality, harmonic closeness centrality, betweenness centrality, and eigenvector centrality—were calculated. The top 20 cities for each centrality measure were identified and ranked accordingly, as detailed in Appendix Tables 1–3. These rankings provide a comparative overview of the most influential cities within the network based on different centrality perspectives.

1) Degree centrality

Degree centrality, which quantifies the number of direct connections each city has within the network, highlights the prominence of key cities in maintaining national connectivity. In the aviation network, Beijing, Shanghai, and Xi'an emerge as the most connected cities, serving as the country's major aviation hubs with extensive reach. Similarly, in the HSR sub-network, Beijing, Shanghai and Guangzhou exhibit the highest degree centrality, indicating their crucial role in upholding the connectivity and robustness of both the HSR and the integrated air-HSR transport network. Regionally, cities like Kunming, Guangzhou, Chengdu and Chongqing are pivotal in their respective aviation networks, while Zhengzhou, Changsha, Nanjing and Hangzhou hold significant roles within the HSR network, ensuring regional accessibility and strengthening the cohesion of the national network. Notably, some cities with less prominence in the air network, such as Jinan, Xuzhou, Fuzhou, and Wuxi, are important HSR hubs. For instance, Xuzhou and Wuxi, despite having smaller airports, benefit from well-developed HSR connections. The degree centrality rankings of the air-HSR intermodal network align more closely with those of the HSR network, suggesting that cities on rail routes contribute more significantly to the overall connectivity of hub cities in terms of the number of connected cities.

2) Weighted degree centrality

Weighted centrality evaluates the national connectivity of each city by considering the frequency of services operated. When assessed through weighted degree centrality, Shanghai, Beijing, and Guangzhou emerge as the most connected cities in China for both air and HSR transport, not only due to their extensive links to numerous other cities but also because of the high frequency of services to and from each destination. This high service density offers travellers greater convenience and a wider selection of departure times. Interestingly, while Urumqi and Haikou rank among the top 20 cities in terms of degree centrality, they do not appear in the top 20 for weighted degree centrality. This suggests that these cities prioritise expanding their network to connect with more cities rather than increasing the frequency of services, highlighting a strategic emphasis on connectivity over convenience. The contrast between these two centrality measures reflects the varying strategic priorities of different cities in network expansion. The weighted centrality rankings for the intermodal network align with the characteristics of the two sub-networks, where the top cities, such as Xi'an and Kunming, demonstrate higher flight frequencies, while others

like Nanjing and Changsha exhibit higher HSR frequencies.

3) Harmonic closeness centrality

Harmonic closeness centrality assesses a city node's capacity for independent transportation, indicating its ability to facilitate transport without depending on other cities. A higher harmonic closeness centrality value reflects a shorter average path length between the city and other nodes, suggesting stronger inter-city connectivity. In the aviation network, aside from Beijing and Shanghai, cities like Xi'an, Kunming, and Guangzhou are among the top five in closeness centrality. Similarly, in the HSR network, Beijing and Shanghai are joined by Nanjing, Changsha, and Suzhou in the top five. When the two sub-networks are combined into the intermodal network, Beijing, Shanghai, and Guangzhou occupy the top three positions, with Zhengzhou and Xi'an rounding out the top five. This indicates that these cities have the shortest average travel distances to other domestic cities and possess robust independent connectivity capabilities. Additionally, cities such as Chongqing, Chengdu, Changsha, Nanjing, and Shenzhen also demonstrate high levels of efficiency in national connectivity, ensuring effective regional and nationwide transport integration.

4) Betweenness centrality

Betweenness centrality evaluates a city node's capacity to serve as a transit hub, facilitating transportation between other city nodes. A higher betweenness centrality value indicates a stronger ability of a city to function as an intermediary point in transport flows. In both the national aviation and intermodal networks, Beijing, Xi'an, and Kunming are the cities with the highest transit capacities. In the HSR network, Beijing, Shanghai, and Guangzhou occupy the top three positions, underscoring their critical role in bridging connections between other cities. Notably, cities such as Urumqi, Hohhot, and Lanzhou, which rank relatively low in closeness and degree centrality, display high betweenness centrality. This suggests that although these cities may not have the highest direct connectivity or proximity, they serve as significant transit hubs, linking major cities with smaller regional centres and thereby enhancing the overall connectivity of the network. Their strategic position as intermediaries is crucial in maintaining the cohesion and efficiency of the national transport network.

5) Eigenvector centrality

Eigenvector centrality assesses a city's influence within the network by considering the quality of its connections to other influential nodes. Cities such as Beijing, Shanghai, Guangzhou, Zhengzhou, Changsha, and Xi'an not only have strong individual connectivity but are also linked to other cities with substantial influence, thereby amplifying their overall significance within the network. These hubs exert considerable influence and reinforce their roles by connecting with other key nodes. In the sub-network rankings, cities like Haikou, Xiamen, Shenyang, and Xuzhou may not exhibit high centrality in terms of direct connections, but they enhance their influence in the network by strategically linking to important hubs. This strategic positioning allows them to play an influential role in the broader network.

Overall, Beijing consistently ranks highly across all centrality measures, underscoring its role as the most vital node within China's integrated air-HSR network. It is distinguished by its strong connectivity (degree centrality), substantial influence (eigenvector centrality), and critical role in transit traffic (betweenness centrality). Similarly, Shanghai and Guangzhou also perform exceptionally well across all centrality metrics, confirming their status as central hubs within the network and their capacity to manage significant traffic volumes. Xi'an, Kunming, and Zhengzhou exhibit particularly high betweenness centrality, highlighting their strategic importance as transit points that connect developed eastern regions with other parts of the country,

playing a crucial role in integrating less developed western regions into the national economy. Meanwhile, Chengdu and Chongqing demonstrate a balanced performance across various centrality indicators, reflecting their growing significance as key nodes in the transport network of western China.

5. Cluster analysis

Building on the centrality analysis, the next step involves a detailed examination of the network's structural properties through cluster analysis. To gain a deeper understanding of the roles and interactions of different cities within China's air sub-network, HSR sub-network, and the integrated air-HSR network, two clustering methodologies — K-means clustering and Agglomerative Hierarchical Clustering (AHC)—are employed respectively for each network type. Both methods utilise the centrality measures calculated in the previous section—degree centrality, weighted degree, harmonic closeness centrality, betweenness centrality, and eigenvector centrality—to identify patterns and groupings within the network. The analyses are performed using the XLSTAT statistical software tool, which enables a detection of clustering outcomes and the relationships between cities based on their centrality characteristics.

K-means clustering in XLSTAT is a robust method for partitioning datasets into K distinct clusters based on feature similarity, optimising within-cluster variance while maximising between-cluster variance. The methodology involves initialising K centroids, iteratively assigning each data point to the nearest centroid (Euclidean distance), and recalculating centroids based on cluster memberships until convergence (Steinley, 2006). In parallel, AHC offers a complementary approach by grouping cities in a hierarchical fashion based on dissimilarities. AHC starts by treating each city as its own cluster and progressively merges clusters based on their proximity until the desired number of clusters is achieved (Bouguettaya et al., 2015). By employing both K-means and AHC, this study uncovers regional connectivity patterns while addressing the limitations of prior clustering approaches that often rely on a single methodology. This dual-method approach allows for cross-validation of clustering results and provides a more comprehensive perspective on the structural and functional differentiation within and across the networks.

5.1. K-means clustering results

5.1.1. K-means clustering for air sub-network

Firstly, cluster analysis was performed on 187 cities within China's air network using all the centrality measures calculated from the previous section, and each centrality indicator is equally weighted. The silhouette score was employed to evaluate the quality of clustering. The score is a metric used to evaluate the quality of a clustering result in data analysis. It provides an assessment of how similar an object is to its own cluster (cohesion) compared to other clusters (separation), with higher scores indicating more well-defined clusters (Rousseeuw, 1987). Fig. 12 revealed that the highest silhouette score was achieved with a two-cluster solution, suggesting that this configuration provides the most distinct and well-separated clusters within the network. As the number of clusters increased beyond two, the silhouette score decreased, indicating that additional clusters could lead to over-segmentation, thereby diminishing the clarity and cohesiveness of the cluster structure.

Cluster 1 comprises 11 cities—Beijing, Shanghai, Guangzhou, Chengdu, Xi'an, Kunming, Chongqing, Shenzhen, Harbin, Hohhot, and Urumqi, as shown in Fig. 13. These cities serve as major hubs within the aviation network, characterised by high centrality values across several measures, which highlights their role as key nodes essential for maintaining air traffic flow and connectivity. The cities in this cluster exhibit

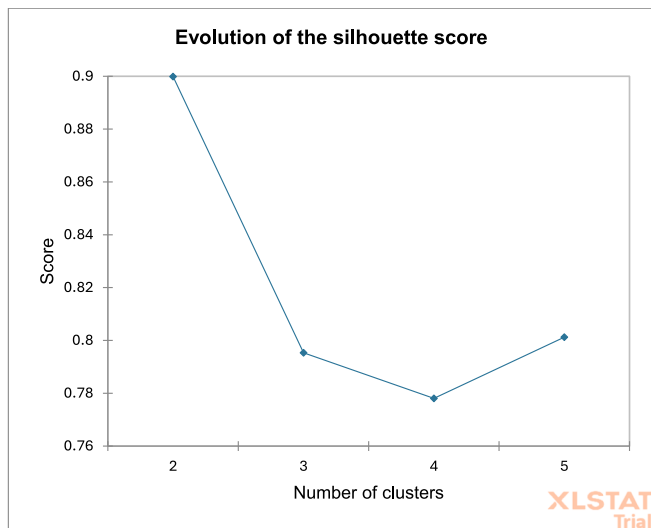


Fig. 12. Silhouette score in K-means cluster analysis for air network.



Fig. 13. Major hubs identified in K-means cluster analysis for air network.

high within-cluster variance, reflecting their diverse and influential positions in the network. Notably, this cluster aligns with previous topological and centrality analyses, as well as the ten international aviation hub cities designated by the [Civil Aviation Administration of China \(2023\)](#), with the inclusion of Hohhot underscoring its strategic importance in linking cities within the Inner Mongolia region to the national network.

In contrast, Cluster 2 consists of 176 cities with lower within-cluster variance and a more uniform network role, representing less central, more homogeneous cities in terms of their connectivity. This distinction highlights the hierarchical structure of China's aviation network, where a few hub cities function as pivotal nodes that facilitate air traffic flows and connect various regions across the country.

5.1.2. K-means clustering for HSR sub-network

Similarly, in the analysis of the HSR network, the cluster results reveal two distinct groups of cities, as shown in Fig. 14. Cluster 1 comprises 24 cities, including major metropolitan hubs such as Beijing, Shanghai, Guangzhou, and Xi'an, predominantly located in the eastern region, as shown in Fig. 15. These cities exhibit significantly higher intra-cluster variance and mean distance to the centroid, indicating considerable differences in their central roles within the network. As key nodes in the HSR network, these cities function as major hubs with extensive connectivity and influence. The substantial variation within this cluster suggests that while all these cities are important, some are markedly more influential than others, highlighting a hierarchy even

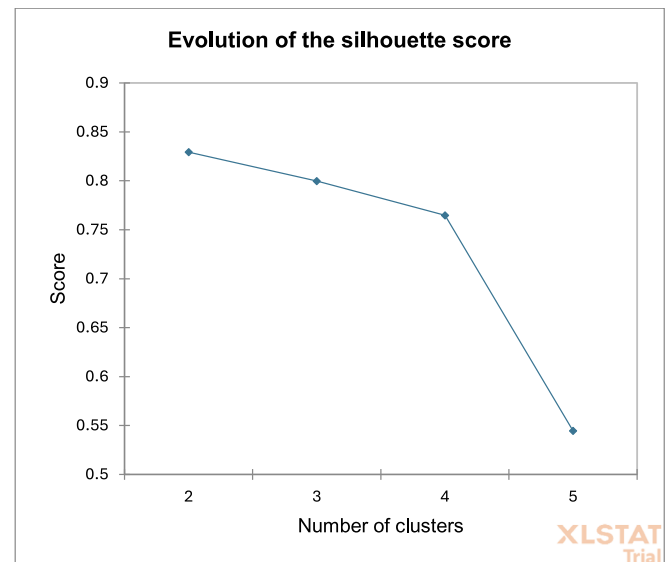


Fig. 14. Silhouette score in K-means cluster analysis for HSR network.



Fig. 15. Major hubs identified in K-means cluster analysis for HSR network.

among the top cities.

In contrast, Cluster 2 includes 227 cities, characterised by much lower intra-cluster variance and a shorter average distance to the centroid. This reflects a more homogeneous group of cities that generally occupy less important positions within the network. Cities in Cluster 2 primarily serve local functions, acting as feeders or endpoints to the broader HSR network. Their overall connectivity and influence are more limited compared to the cities in Cluster 1, underscoring a clear distinction between the central and peripheral roles played by different cities within the HSR network.

5.1.3. K-means clustering for air-HSR integrated network

For the integrated air-HSR network, the cluster analysis reveals a similarly clear distinction between a small group of highly central cities (Cluster 1) and a larger group of less central cities (Cluster 2). The

silhouette scores validate the two-cluster solution as optimal, effectively distinguishing major hubs from the rest of the cities in a meaningful way (See Fig. 16). This analysis further underscores the hierarchical structure of the integrated network, characterised by a few key cities that dominate in terms of centrality and connectivity, while the majority of cities fulfil more localised roles.

Specifically, Cluster 1 in the integrated network consists of 13 cities, which are from the cities identified as Cluster 1 in the two sub-networks: Shenzhen, Shanghai, Beijing, Guangzhou, Chengdu, Chongqing, Kunming, Xi'an, Nanjing, Harbin, Urumqi, Changsha, and Zhengzhou (shown in Fig. 17). This grouping adds three significant HSR cities—Nanjing, Changsha, and Zhengzhou—to the major air hub cities identified in the aviation network cluster analysis, while Hohhot is excluded due to its limited HSR connections in Inner Mongolia. The cities in this cluster represent the core metropolitan hubs of the integrated air-HSR network. The variability in centrality indicators among these cities indicates their diverse roles within the network, showing their high levels of connectivity and influence. These cities are essential for maintaining the network's efficiency and effectiveness, facilitating connections across all regions of China.

In contrast, Cluster 2 comprises 315 cities that represent the more peripheral cities within the network. These cities exhibit greater uniformity in their centrality indicators, suggesting they primarily serve supportive roles in regional connectivity rather than functioning as major hubs. While they form the foundational backbone of the network by providing extensive geographic coverage, individual cities in this cluster do not display the same level of centrality as those in Cluster 1. This distinction reinforces the network's hierarchical structure, where a small number of central cities play a dominant role in national connectivity, while the majority ensure regional and local connections.

5.2. Agglomerative hierarchical clustering results

5.2.1. Agglomerative hierarchical clustering for air sub-network

The hierarchical clustering of the air network has produced three distinct clusters, shown in Fig. 18. The Hartigan Index difference is strongest between 2 and 3 clusters, highlighting a significant improvement when moving to 3 clusters. Cluster 1 contains 5 cities - Beijing, Shanghai, Xi'an, Kunming, and Urumqi, as shown in Fig. 19. These cities exhibit the highest centrality measures, with significantly greater values in degree centrality and weighted degree compared to other clusters. Their high within-cluster variance and average distance to the centroid

reflect the diverse roles these cities play in the network, ranging from national hubs to critical transit points. These cities form the core nodes of the air network. Their roles are consistent with their performance in other centrality analyses, where they dominate in terms of connectivity, influence, and transit capabilities.

Cluster 2 contains 17 cities, including major hubs such as Guangzhou, Chengdu, Shenzhen, and Hangzhou. This cluster is characterised by moderate centrality values. The degree centrality and weighted degree are lower than Cluster 1 but significantly higher than Cluster 3. These cities represent regional hubs and connectors. Their centrality measures suggest that they facilitate regional traffic while also maintaining some degree of national influence. The cluster has a relatively lower within-cluster variance compared to Cluster 1, indicating more homogeneity in network roles among these cities.

Cluster 3 contains 165 cities, accounting for the majority of cities in the network. Centrality values are much lower. These cities are peripheral nodes in the network, playing supportive roles in ensuring broader coverage but lacking significant influence or connectivity. The cluster has the lowest within-cluster variance, reflecting their uniform and less influential role in the network.

5.2.2. Agglomerative hierarchical clustering for HSR sub-network

The hierarchical clustering of the HSR network also identified three distinct clusters, as shown in Fig. 20. Cluster 1 comprises three cities: Beijing, Shanghai, and Guangzhou. These cities stand out as super hubs with exceptionally high centrality metrics across all dimensions. For instance, they exhibit a degree of 220, weighted degree of 3367.67, and eigenvector centrality of 0.909, far surpassing the metrics of other clusters. These cities are pivotal for the national connectivity of the HSR network. Their high betweenness centrality (average of 5131.96) underlines their critical role in facilitating inter-regional travel and acting as transit hubs. The substantial within-cluster variance and large distances to the centroid reflect the unique and dominant roles of these cities in the network.

As shown in Fig. 21, cluster 2 includes 31 cities such as Zhengzhou, Nanjing, Hangzhou, and Chengdu. These cities function as secondary hubs, with metrics such as a degree of 117.94 and weighted degree of 1035.66. While their centrality metrics are not as high as those in Cluster 1, they still exhibit significant regional influence and serve as important connectors between major hubs and smaller cities. The betweenness centrality (1146.95) indicates their role in linking different regions, and the eigenvector centrality (0.58) suggests their connectivity to influential nodes in the network. This cluster reflects the intermediate layer of the HSR network, bridging the super hubs and peripheral nodes.

Cluster 3, the largest group with 217 cities, consists of peripheral nodes such as Jiaxing, Jinhua, and Ganzhou. These cities exhibit relatively low centrality metrics. Their roles are more localised, contributing to regional connectivity rather than serving as key transit points. The low eigenvector centrality indicates their limited connectivity to influential nodes, while the small within-cluster variance and shorter distances to the centroid highlight the homogeneity of this cluster. These cities form the branches of the HSR network by extending its coverage and ensuring accessibility to less-developed areas.

5.2.3. Agglomerative hierarchical clustering for air-HSR integrated network

The Agglomerative Hierarchical Clustering (AHC) analysis for the air-HSR integrated network identifies two distinct clusters based on centrality measures, as shown in Fig. 22 and as indicated by the highest difference in the Hartigan index. These two clusters matches the K-means clustering and reflect a clear hierarchical structure in the integrated network.

Cluster 1 comprises seven cities: Beijing, Shanghai, Guangzhou, Xi'an, Chongqing, Chengdu, and Kunming, as shown in Fig. 23. All of these cities are also cluster 1 hubs for K-means clustering. These cities are the most connected nodes in the integrated network, showing exceptionally high values in all centrality measures, including degree

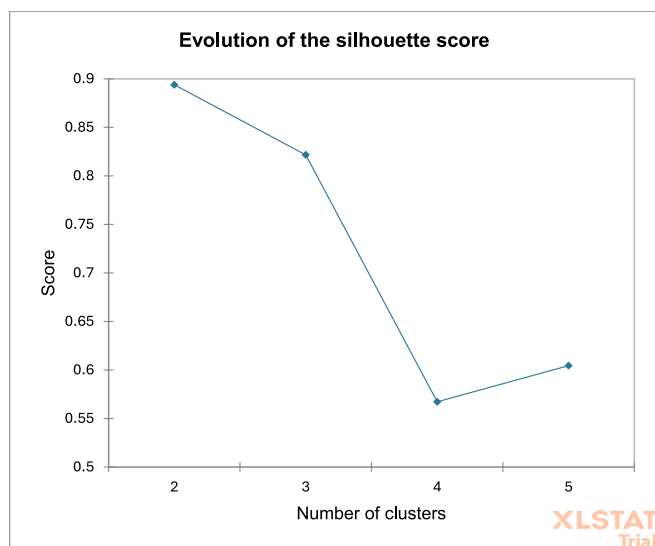


Fig. 16. Silhouette score in K-means cluster analysis for air-HSR integrated network.



Fig. 17. Major hubs identified in K-means cluster analysis for air-HSR integrated network.

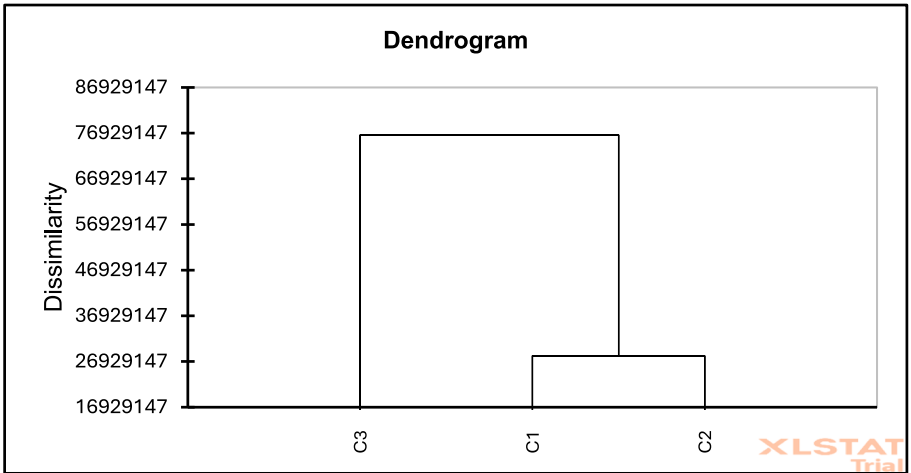


Fig. 18. Dissimilarity identified in AHC analysis for air network.

(181.29), weighted degree (2333.43), harmonic closeness centrality (0.75), betweenness centrality (3966.50), and eigenvector centrality (0.87). These cities act as national hubs, combining extensive air and HSR connections to facilitate both regional and national connectivity. Their high betweenness centrality underscores their critical role as transit nodes, while their high eigenvector centrality indicates their influence within the broader network.

Cluster 2 consists of 321 cities, including Zhengzhou, Hangzhou, Shenzhen, Nanchang, and others. These cities display significantly lower centrality values across all metrics, with an average degree of 30.38, weighted degree of 189.20, and betweenness centrality of 112.52. These cities primarily serve as regional hubs or connectors, supporting localised connectivity and acting as feeders to the larger hub cities in Cluster 1. Their roles are crucial for enhancing accessibility within their respective regions but lack the national-level influence observed in Cluster 1.

6. Discussion

6.1. Structural characteristics of the networks

The analysis of China’s aviation, HSR sub-networks, and the integrated air-HSR network reveals distinct structural characteristics that align with, but also diverge from, global patterns. All three networks exhibit small-world properties, characterised by high clustering coefficients and short average path lengths, which enhance connectivity and efficiency across regions. However, none of these networks conform to the traditional scale-free properties often observed in global transport networks, such as the power-law degree distribution found in studies like Guimerà et al. (2005). Instead, China’s networks exhibit a truncated degree distribution. This rapid decay beyond a certain connectivity threshold—faster than typical power-law distributions—can be attributed to operational capacity constraints at airports and the geographical limitations of the HSR tracks, as well as diminishing returns for small and medium-sized cities once they establish connections to approximately 50 domestic cities, which suffice for their travel and economic

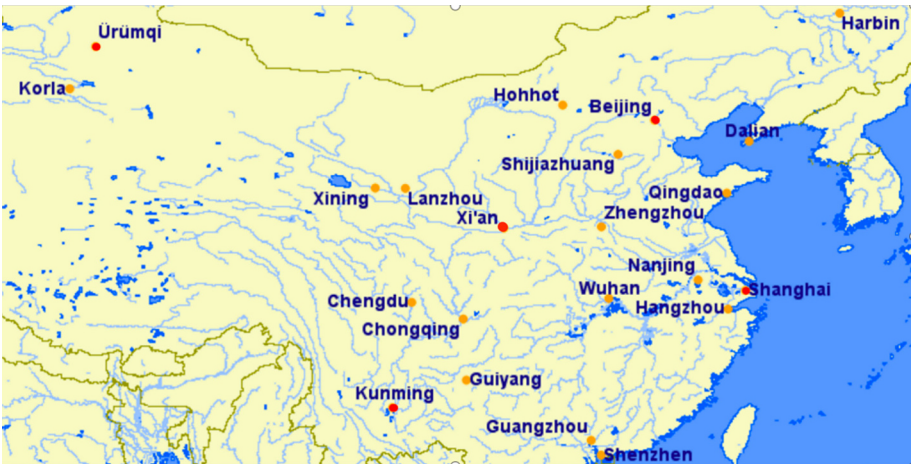


Fig. 19. Cluster 1 (red) and cluster 2 (orange) cities identified in AHC analysis for air network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

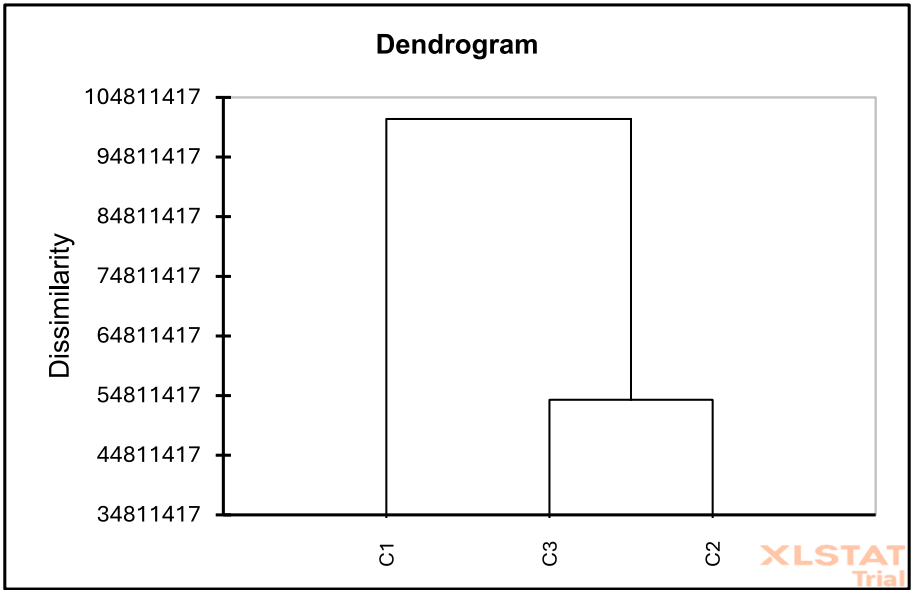


Fig. 20. Dissimilarity identified in AHC analysis for HSR network.

needs.

In comparison, global air networks often demonstrate pronounced hub dominance, as seen in scale-free properties, where major airports maintain disproportionate importance in connectivity and resilience. Similarly, European aviation networks, as studied by [Lordan et al. \(2014\)](#), exhibit a double Pareto distribution reflecting the integration of multiple national networks, leading to a more diverse structural pattern than China's unified, policy-driven development trajectory. By contrast, China's integrated air-HSR network balances the regional focus of the HSR sub-network with the broader national connectivity provided by the aviation network. This integration achieves high small-world efficiency but highlights the need for addressing capacity bottlenecks and planning to enhance intermodal integration.

6.2. Dual strengths and trade-offs in the integrated network

While previous research has extensively examined efficiency through metrics such as shortest path length and clustering coefficients, fewer studies have incorporated resilience measures like modularity and node criticality. Our dual-lens evaluation demonstrates that the integrated network enhances connectivity by reducing average path length and increasing clustering, leveraging aviation's direct long-distance connectivity and HSR's dense regional accessibility. This dual functionality fosters economic integration along key corridors and improves national mobility. However, these efficiency gains come with resilience challenges. The network's lower modularity reduces compartmentalisation, potentially amplifying the impact of disruptions, while the increased reliance on high-centrality nodes, such as major hubs, makes the system vulnerable to failures at these critical points.

The clustering results provide additional patterns for the hierarchical and regional structure of the integrated network. The air network is characterised by a more centralised structure dominated by a few highly connected major hubs, which serve as pivotal nodes for long-distance national and international travel. These hubs act as the backbone of the national network, ensuring connectivity across vast geographic distances and integrating China with global transportation systems. Conversely, the HSR network is structured to prioritise regional accessibility, with its connectivity distributed along economic corridors, such as the Beijing-Shanghai and Wuhan-Guangzhou routes. This regionally distributed, corridor-oriented structure enables regional hubs, including



Fig. 21. Cluster 1 (red) and cluster 2 (orange) cities identified in AHC analysis for HSR network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

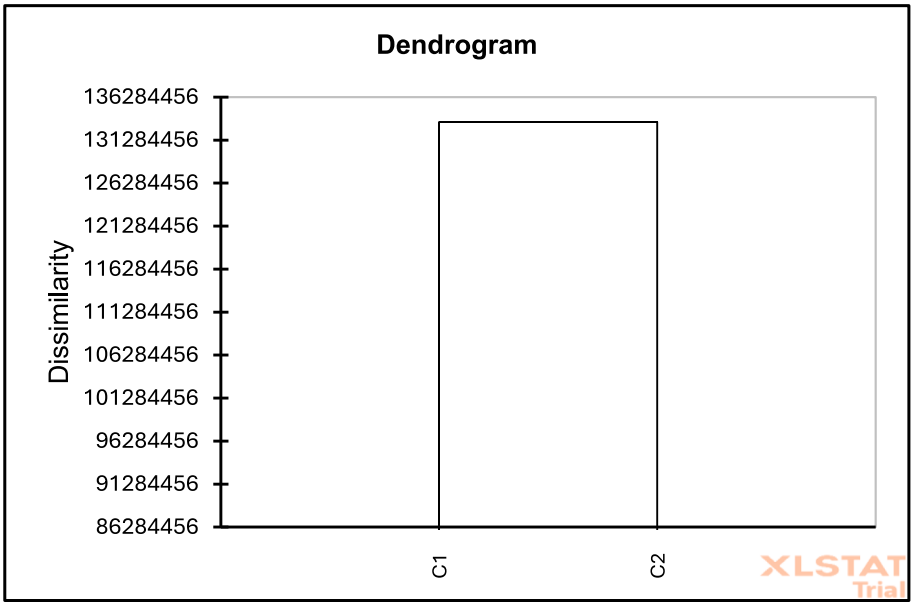


Fig. 22. Dissimilarity identified in AHC analysis for air-HSR integrated network.



Fig. 23. Cluster 1 hub cities identified in AHC analysis for air-HSR integrated network.

Zhengzhou, Changsha, and Xi'an, to act as critical nodes in facilitating efficient movement within and across regions.

6.3. Regional impacts of integration

The integration of air and HSR networks significantly enhances connectivity for cities that currently have limited access to one or both modes of transportation. For instance, results from the centrality and cluster analyses indicate that cities like Zhengzhou and Changsha gain substantial benefits from integration due to their strategic roles as regional hubs. These cities exhibit notable improvements in overall centrality and connectivity metrics, as HSR connections effectively complement their relatively limited air connections. Conversely, major hubs such as Beijing, Shanghai, and Guangzhou, already highly connected within both sub-networks, experience marginal gains in connectivity from integration.

Moreover, the integrated network demonstrates a unique pattern of modularity that combines the centralised structure of the aviation network with the more decentralised, regionally focused structure of the HSR network. This results in a hybrid modular structure where some regions exhibit tight communities around key nodes (as seen in the HSR network), while others are more loosely connected through major hub cities (as observed in the aviation network). This hybrid modularity enhances the network's ability to adapt to varying levels of demand and regional development needs, offering a flexible approach to managing connectivity across different parts of the country.

6.4. Broader considerations for integration

Topological analysis in complex networks traditionally focuses on spatial connectivity and structural relationships between nodes, rather than on qualitative metrics like speed or price. Although speed, price, and transport volume were not directly included in the network construction, their significance in characterising air and HSR networks warrants further discussion. The disparities in speed, pricing structures, and capacity across the two modes influence passenger preferences and

operational strategies. For example, air transport excels in long-distance travel due to higher speeds, while HSR offers competitive travel times on short to medium-distance routes, particularly for city-centre to city-centre travel. HSR often provides more cost-effective options for passengers compared to air travel, especially for shorter distances or in regions where low-cost carriers are less prevalent. Besides, HSR networks have higher passenger capacity per trip, making them well-suited for high-demand corridors, whereas air transport offers greater flexibility in adjusting capacity through variable flight frequencies and aircraft sizes. The integration of these metrics into future analyses could provide deeper insights into the complementary roles of air and HSR networks.

7. Policy recommendations

Based on the findings from topological analysis, centrality measures, and cluster analysis, this section discusses key implications and proposes practical policy recommendations for improving the resilience, connectivity, and balance of China's integrated air-HSR network.

7.1. Balancing network resilience and expansion

The integrated air-HSR network in China offers significant potential for balancing efficiency and resilience. It achieves efficiency gains through reduced average path length, higher clustering coefficients, and increased centrality measures, while its dual functionality allows for enhanced redundancy and more effective demand distribution. However, these improvements come with resilience tradeoffs, particularly due to heightened dependence on high-centrality nodes and reduced modularity, which increase vulnerability to disruptions.

To address these challenges, policies should adopt a multi-tiered approach. For major hub cities (e.g., Beijing, Shanghai, Guangzhou) that dominate national connectivity but face capacity saturation, infrastructure upgrades and capacity management strategies are critical. Strengthening these hubs will help redistribute traffic and reduce congestion risks. At the same time, policies should aim to bolster the role

of secondary hubs, such as Zhengzhou, Xi'an, and Changsha, as regional connectors. By enhancing their capacity and integrating them into alternative routing systems, these cities can provide redundancy, improve resilience, and alleviate pressure on super hubs. Additionally, for peripheral or less-connected cities, integrating them into the broader network can improve regional accessibility and promote equitable development, fostering a more balanced and inclusive system.

7.2. Addressing regional disparities

Cluster analyses indicate significant regional imbalances in connectivity, with most high-centrality cities concentrated in the eastern regions of China. The hierarchical structure of the HSR network particularly highlights the need to enhance connectivity in under-served western regions. Policies should focus on strengthening the roles of Cluster 3 cities in the west and providing subsidies for expanding HSR lines and air routes in these areas. Developing regional feeder routes for Cluster 2 cities can ensure a diffusion effect, spreading the benefits of economic development from well-connected regions to less developed areas.

The siphon effect observed in major hubs like Beijing and Shanghai underscores the importance of balanced investment strategies. Promoting direct connections between secondary cities in the west and other regions can reduce reliance on congested eastern hubs and distribute traffic more evenly across the network.

7.3. Differentiated strategies for air and HSR networks

The distinct structural characteristics of air and HSR networks necessitate differentiated policy approaches. For air network, policies should concentrate on long-haul and international connectivity, leveraging the flexibility and speed advantages of aviation. Cluster 1 cities in the air network, such as Beijing and Shanghai, require policies to optimise slot allocation and expand international routes. Simultaneously, developing regional airports and incentivising airlines to establish direct flights between secondary cities (Cluster 2 and 3 cities) can improve accessibility and reduce reliance on overburdened hubs.

For the HSR network, policies should enhance regional integration and medium-distance connectivity, particularly in economic corridors. Cluster 2 cities, such as Zhengzhou and Changsha, should be strengthened as regional hubs through investments in infrastructure and service frequency optimisation. Additionally, HSR expansion in western regions should prioritise integrating under-connected cities (Cluster 3) into national corridors.

Integrating these approaches with the complementary strengths of air and HSR networks provides additional opportunities. For instance, regional hubs with dense HSR networks but sparse air connections, such as Xuzhou and Jinan, could prioritise increasing air connections or flight frequencies to expand their long-distance travel options. Conversely, cities with strong air connectivity but less-developed HSR links, such as Hohhot and Urumqi, would benefit from strengthening HSR networks to improve regional accessibility and relieve pressure on the air network.

7.4. Enhancing intermodal integration

The integrated air-HSR network demonstrates superior connectivity and clustering characteristics, highlighting its potential for intermodal synergies. However, the integration is hindered by operational disparities and the absence of schedule synchronisation, which limits the seamless transfer of passengers between modes. To maximise the benefits of the integrated network, targeted policies are needed to address these challenges by developing seamless intermodal hubs, integrating ticketing and scheduling systems, and implementing dynamic pricing and capacity coordination.

Cluster 1 cities in the integrated network, such as Beijing and Guangzhou, serve as critical hubs for national connectivity. Policies

should prioritise the development of seamless intermodal hubs with integrated facilities that support efficient transfers between air and HSR. Building HSR stations adjacent to airports in these cities can enhance passenger convenience by reducing transfer times and improving travel experiences. For Cluster 2 cities, such as Zhengzhou and Xi'an, improving feeder routes and intermodal coordination can strengthen their roles as regional hubs while reducing reliance on overburdened major hubs.

The absence of schedule synchronisation between air and HSR services remains a barrier to seamless connectivity. To address this, unified scheduling platforms should be developed to align flight arrivals with train departures (or train arrivals with flight departures), minimising transfer times and optimising connectivity. Establishing guidelines for intermodal schedule integration in key hubs and incentivising airlines, airports, HSR stations and operators to collaborate on joint planning efforts are crucial steps. By implementing transfer-friendly schedules, passengers can enjoy a unified travel experience that leverages the strengths of both networks.

Operational disparities in speed, price, and capacity require thoughtful strategies to maximise the complementary strengths of air and HSR networks. Dynamic pricing strategies can reflect demand elasticity, encouraging mode shifts to alleviate congestion in air networks and increase HSR utilisation. For instance, discounted HSR fares during peak air travel times can optimise capacity across both modes. Coordinated capacity planning, informed by joint demand forecasting, can prevent over-supply in one network and under-utilisation in another, ensuring balanced infrastructure investments.

8. Conclusion

This paper presents a comprehensive complex network analysis of China's integrated air-HSR network by constructing a directed weighted network and comparing the complex characteristics of the integrated network with its sub-networks. Unlike previous studies that primarily focus on single networks, this research breaks new ground by integrating both air and HSR networks to form an intermodal network. While all three networks demonstrate small-world properties, they diverge from the traditional scale-free patterns, exhibiting instead a truncated degree distribution shaped by operational constraints and market saturation.

The integration of air and HSR networks achieves a delicate balance between aviation's broad national and international connectivity and HSR's regionally focused accessibility. This integration enhances network efficiency by reducing average path lengths and increasing clustering, while simultaneously fostering economic integration and connectivity for cities across China. However, the reliance on high-centrality nodes introduces resilience trade-offs, as disruptions at key hubs could significantly impact network functionality.

Furthermore, the integrated network's hybrid modularity underscores its adaptability to diverse regional development needs. By combining the centralised structure of aviation with the decentralised, corridor-oriented nature of HSR, the system offers a flexible approach to managing connectivity. Regional hubs, such as Zhengzhou and Changsha, emerge as critical beneficiaries of this integration, while already well-connected major cities experience only marginal gains.

While this study provides a comprehensive analysis of China's integrated air-HSR network, one limitation is the use of static data, due to the availability of the HSR data, representing the latest status before Covid. This approach does not account for temporal dynamics or changes in network structure over time, such as those driven by policy shifts, economic development, or infrastructural upgrades. Future research could adopt a longitudinal approach, analysing how the network evolves over time and how these changes affect its topological and centrality characteristics.

CRediT authorship contribution statement

Mengyuan Lu: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Edgar Jimenez Perez:** Writing – review & editing, Supervision. **Keith Mason:** Writing –

review & editing, Supervision.

Declaration of competing interest

The authors declare no conflicts of interest.

Appendix A

Appendix Table 1
Centrality measurement rankings for air sub-network.

Rank	City	Degree	City	Weighted degree	City	Harmonic closeness	City	Betweenness	City	Eigenvalue
1	Beijing	181	Shanghai	1371	Beijing	0.7414	Beijing	5228.33	Beijing	1.0000
2	Shanghai	158	Beijing	1313	Shanghai	0.7090	XiAn	3899.16	Shanghai	0.9667
3	XiAn	149	Guangzhou	978	XiAn	0.7009	Kunming	3892.07	Guangzhou	0.9487
4	Kunming	144	Kunming	821	Kunming	0.6883	Shanghai	3646.33	Chengdu	0.9324
5	Guangzhou	140	Chengdu	810	Guangzhou	0.6847	Urumqi	3302.06	XiAn	0.9241
6	Chengdu	132	Shenzhen	802	Chengdu	0.6766	Chengdu	2545.66	Kunming	0.9183
7	Chongqing	132	XiAn	801	Chongqing	0.6730	Chongqing	2237.71	Chongqing	0.8939
8	Shenzhen	129	Chongqing	722	Shenzhen	0.6694	Hohhot	2211.48	Shenzhen	0.8506
9	Hangzhou	102	Hangzhou	605	Hangzhou	0.6306	Shenzhen	2031.99	Changsha	0.7905
10	Guiyang	98	Nanking	513	Changsha	0.6225	Harbin	1892.02	Hangzhou	0.7746
11	Changsha	96	Zhengzhou	495	Wuhan	0.6171	Guangzhou	1666.28	Wuhan	0.7455
12	Wuhan	92	Wuhan	460	Nanking	0.6162	Lanzhou	1308.71	Guiyang	0.7452
13	Harbin	91	Urumqi	453	Zhengzhou	0.6162	Guiyang	1138.19	Nanking	0.7430
14	Nanking	90	Changsha	438	Guiyang	0.6153	Xining	971.58	Haikou	0.7169
15	Zhengzhou	90	Xiamen	411	Qingdao	0.6090	Hangzhou	932.67	Taiyuan	0.7039
16	Qingdao	86	Guiyang	398	Hohhot	0.6090	Wuhan	914.20	Qingdao	0.7014
17	Dalian	86	Qingdao	392	Harbin	0.6036	Shijiazhuang	887.78	Zhengzhou	0.6996
18	Hohhot	84	Haikou	375	Urumqi	0.5982	Korla	847.67	Xiamen	0.6875
19	Shenyang	82	Harbin	342	Taiyuan	0.5964	Qingdao	826.63	Harbin	0.6825
20	Xiamen	81	Dalian	332	Tianjin	0.5946	Dalian	815.59	Shenyang	0.6768

Appendix Table 2
Centrality measurement rankings for HSR sub-network.

Rank	City	Degree	City	Weighted degree	City	Harmonic closeness	City	Betweenness	City	Eigenvalue
1	Beijing	243	Shanghai	3989	Beijing	0.6924	Beijing	7897.86	Beijing	1.0000
2	Shanghai	225	Guangzhou	3600	Shanghai	0.6830	Shanghai	3770.16	Shanghai	0.9463
3	Guangzhou	192	Beijing	2514	Nanking	0.6675	Guangzhou	3727.87	Zhengzhou	0.8527
4	Zhengzhou	191	Shenzhen	2048	Changsha	0.6521	Zhengzhou	3284.20	XiAn	0.8190
5	Changsha	184	Nanking	2036	Suzhou	0.6521	Changsha	2952.85	Changsha	0.7976
6	Nanking	167	Changsha	1588	Zhengzhou	0.6486	Chengdu	2191.30	Chongqing	0.7907
7	Hangzhou	161	Chengdu	1504	Wuxi	0.6478	Nanking	2177.78	Guangzhou	0.7808
8	Jinan	157	Hangzhou	1411	Hangzhou	0.6426	Lanzhou	2147.49	Hangzhou	0.7712
9	Chongqing	154	Fuzhou	1383	Guangzhou	0.6400	Kunming	1894.70	Fuzhou	0.7633
10	Chengdu	153	Xiamen	1275	Jinan	0.6400	Shenzhen	1818.51	Chengdu	0.7507
11	Shenzhen	146	XiAn	1213	Changzhou	0.6332	Jinan	1782.57	Jinan	0.7243
12	Fuzhou	138	Chongqing	1203	Xuzhou	0.6160	Guiyang	1541.46	Nanking	0.7225
13	Nanchang	133	Kunming	1154	Wuhan	0.6108	Chongqing	1535.82	Xiamen	0.7015
14	XiAn	127	Zhengzhou	1145	Hefei	0.6082	Nanchang	1254.36	Nanchang	0.6934
15	Kunming	124	Qingdao	1057	Shangrao	0.6082	Hangzhou	1166.86	Kunming	0.6864
16	Xiamen	122	Jinan	1035	Shenzhen	0.6070	Taiyuan	1149.07	Shenzhen	0.6785
17	Guiyang	121	Nanchang	1024	Nanchang	0.6057	Shenyang	1136.92	Nanning	0.6639
18	Xuzhou	119	Nanning	1019	Zhenjiang	0.6034	Wuhan	1018.55	Guiyang	0.6494
19	Tianjin	116	Wenzhou	993	Chengdu	0.5936	Nanning	974.38	Xuzhou	0.6018
20	Qingdao	114	Shenyang	953	Jinhua	0.5924	Dalian	867.92	Qingdao	0.5850

Appendix Table 3
Centrality measurement rankings for air-HSR network.

Rank	City	Degree	City	Weighted degree	City	Harmonic closeness	City	Betweenness	City	Eigenvalue
1	Beijing	243	Shanghai	4187	Beijing	0.8119	Beijing	6620.00	Beijing	1.0000
2	Shanghai	225	Guangzhou	3422	Shanghai	0.7793	XiAn	4381.12	Shanghai	0.9771
3	Guangzhou	192	Beijing	2771	Guangzhou	0.7594	Kunming	3655.98	Guangzhou	0.9021
4	Zhengzhou	191	Shenzhen	2065	Zhengzhou	0.7441	Chengdu	3619.90	Zhengzhou	0.8936

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Appendix Table 3 (continued)

Rank	City	Degree	City	Weighted degree	City	Harmonic closeness	City	Betweenness	City	Eigenvalue
5	Changsha	184	Nanking	1939	XiAn	0.7416	Chongqing	3240.38	Changsha	0.8724
6	Nanking	167	Chengdu	1623	Chongqing	0.7350	Guangzhou	3216.28	XiAn	0.8520
7	Hangzhou	161	XiAn	1594	Chengdu	0.7258	Shanghai	3031.86	Hangzhou	0.8449
8	XiAn	158	Changsha	1487	Changsha	0.7243	Urumqi	2990.01	Chongqing	0.8361
9	Jinan	157	Hangzhou	1400	Nanking	0.7105	Zhengzhou	2346.10	Nanking	0.8357
10	Chongqing	154	Kunming	1375	Shenzhen	0.7090	Harbin	1980.48	Jinan	0.8072
11	Chengdu	153	Chongqing	1362	Hangzhou	0.7074	Hohhot	1733.79	Shenzhen	0.8067
12	Shenzhen	146	Xiamen	1288	Kunming	0.7023	Nanking	1591.47	Chengdu	0.8021
13	Kunming	144	Fuzhou	1212	Jinan	0.6927	Shenzhen	1552.96	Nanchang	0.7465
14	Fuzhou	138	Zhengzhou	1186	Guiyang	0.6631	Changsha	1475.78	Kunming	0.7461
15	Nanchang	133	Qingdao	1041	Tianjin	0.6631	Lanzhou	1295.41	Fuzhou	0.7281
16	Xiamen	122	Jinan	997	Nanchang	0.6621	Guiyang	1149.62	Tianjin	0.7148
17	Guiyang	121	Wenzhou	954	Qingdao	0.6585	Hangzhou	1090.55	Xiamen	0.7127
18	Xuzhou	119	Nanchang	937	Xiamen	0.6570	Shenyang	967.26	Guiyang	0.6868
19	Tianjin	116	Nanning	935	Fuzhou	0.6544	Xining	913.91	Wenzhou	0.6764
20	Qingdao	114	Guiyang	934	Lanzhou	0.6463	Wuhan	866.81	Qingdao	0.6759

Data availability

Data will be made available on request.

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