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Critical review

Fractal assessment analysis of China's air-HSR network integration

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ABSTRACT

High-speed rail (HSR) has emerged as a significant mode for intercity transport in several countries, particularly China, setting an environment that may promote integration between air and HSR networks. To better measure the current level of integration of China's air-HSR intermodal network and identify implementation issues, this paper establishes a novel assessment framework that considers three primary areas: service capability, network connectivity and transfer potential. The framework is based on a comprehensive literature review of network measurement and assessment methodologies. Then, fractal theory is used to establish an assessment model that associates the fractal dimension to the level of intermodal integration, which can serve as an important complement to traditional weighting methods. The model and framework are applied to the 10 cities in China with the potential for air-HSR integration. The results show that international hub airports, together with their closest HSR station, do not necessarily perform at a higher integration level than regional hubs. The paper also proposes policy and practical recommendations to enhance air-HSR network integration levels from service supply, network coordination and transfer design perspectives.

1. Introduction

Since 2008, high-speed rail (HSR) has emerged as a significant transport mode in China after its success in Japan and European countries for several decades (Nunno, 2018). In 2021, China became the country with the highest mileage of HSR track with 40,000 km (ECNS, 2021). At the same time, the growth of HSR in China has forced domestic airlines to cut airfares and cancel regional flights, especially for flights under 500 km. Some of the shorter inter-city routes have been completely terminated (Xu et al., 2016).

Besides the substitution of air by rail (Zhu et al., 2018, 2019), there is also cooperation between the two modes (Albalate et al., 2015; Xia and Zhang, 2016), since the coverage of air routes is broader, especially in mid-western (remote) and international regions of China (Wang et al., 2020). In recent years, some Chinese cities have begun to implement air-HSR intermodal transport initiatives. Hub airports are actively promoting air-HSR intermodal transport to improve their handling capability, expand their radius, relieve capacity pressure and enhance their hub functions. In 2010, Chongqing Airport Group cooperated with Chengdu Railway Bureau to launch the first air-HSR intermodal transport service in China (CNN, 2010). In 2012, China Eastern Airlines and the former Shanghai Railway Bureau launched air-HSR intermodal transport in the Yangtze River Delta, with Shanghai Hongqiao and Pudong airports as the base points of the air hubs and the Yangtze River Delta high-speed rail as the feeder lines, providing intermodal transport services to passengers (CNN, 2012). Since its inauguration in 2012, Shijiazhuang Airport has persistently enhanced its air-HSR connectivity services, providing complimentary and convenient passenger transfer amenities, such as overnight accommodations, luggage storage, and downtown shuttle services (CNN, 2019). However, due to the simplicity of intermodal cooperation, mainly ticketing, and not, for example, scheduling, air-HSR intermodal transport has not been realised at a sizeable scale yet. Even in other countries where air-HSR services are more established, such as the Lufthansa-DB cooperation in Germany (Global Railway Review, 2021), their application remains limited to very few nodes in the combined networks.

To measure and evaluate the extent of intermodal network synergy and identify existing problems, this paper proposes a comprehensive assessment framework of the degree of air-HSR intermodal opportunities that considers three key aspects: service capability, network connectivity and transfer potential. Such framework would lay the foundation for subsequent endeavours in network and infrastructure optimisation. The analysis of the results, along with their implications for policy design, will promote a more efficient and healthy development of air-HSR intermodal transport.

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Based on the assessment framework, this paper adopts fractal theory to evaluate the integration of the air-HSR network. The concept of fractal dimension (explained in detail in Section 3.1.1) captures the degree of irregularity in multidimensional metrics, such as those normally used to assess the integration of air-HSR networks, which requires multiple criteria. The fractal analysis methodology avoids some shortcomings of the commonly used assessment methodologies (He and Ge, 2020), such as Analytic Hierarchy Process (AHP), Fuzzy Comprehensive Evaluation (FCE), or Principal Component Analysis (PCA). By focusing on the spatial distribution of indicators without explicit weighting, fractal analysis provides a holistic view of the intermodal network. This is particularly valuable in cases where the relative importance of indicators may vary across different locations or contexts.

2. Literature review

At present, most scholars analyse multimodality involving air transport and HSR from the following perspectives: feasibility of network integration (Okumura and Tsukai, 2007; Yu and Jiang, 2021); the competitive and cooperative relationship (Albalate et al., 2015; Li et al., 2018; Sato and Chen, 2018; Xia and Zhang, 2016); the overall network and sub-network complexity (Allard and Moura, 2014); social and economical benefits of integration (Huang et al., 2018); assessment of centrality (Wang et al., 2020); and transfer solution (Feng et al., 2021). To the best of the authors' knowledge, no studies have assessed the potential integration of both networks including temporal and spatial considerations, or created an assessment framework to rank and evaluate the combination of air-HSR hubs.

2.1. Measuring the connectivity of air transport networks

Studies on air network connectivity are commonly conducted by academics and industry organisations. In general, the research perspective on air connectivity can be divided into airline network connectivity and airport connectivity. The dimensions studied can be classified as extent, density, time dimension or transfer connectivity. The main indicators measured are accessibility versus centrality, temporal coordination, routing factor, connection quality, the maximum number of steps allowed, local versus global models (Burghouwt and Redondi, 2013), as well as passenger utility (Zhu et al., 2019).

However, most of these measures only consider one aspect of the connection quality such as travel time. More importantly, except for a small number of studies such as Matisziw and Grubesic (2010) and Meire et al. (2019), many of the existing connectivity measures are only constructed for the network of a single transport mode.

2.1.1. Industry perspective

The air-connectivity indicator developed by the International Air Transport Association (IATA) is used to measure the extent to which a country is integrated into the global air transport network. The indicator reflects the number and economic importance of destinations served by a country/region's major airports and the number of onward connections available from each destination. The connectivity indicator is based on the number of available seats per destination (IATA, 2019). The number of available seats for each destination is then weighted according to the size of the destination airport (in terms of the number of passengers handled at that airport each year).

The NetScan airline connectivity model (developed by SEO Aviation Economics and used by ACI Europe) reports airline connectivity scores for individual airports including direct, indirect and total connectivity (ACI, 2018). Direct connectivity is based on the number of destinations served directly and takes into account the frequency of flights. Indirect connectivity measures the number of destinations available via a connecting airport, considering connecting time and detours involved in the indirect routes. NetScan connectivity scores are reported at the airport level and mainly applied in competitive analysis of air networks and the corresponding airports they serve. However this model does not weigh the value of different destinations and some airlines argue this approach is not appropriate for them (Mason et al., 2015).

The World Bank's air-connectivity index shows a country's ability to connect to other countries in a given network. The World Bank developed the Air Connectivity Framework to take into account the hub-and-spoke nature of the global air transport network, with air connectivity scores reported at the country level considering two factors: the strength of the overall ‘pull’ it exerts on the rest of the network, and the cost of travelling to other countries by air. The measure of connectivity is closely correlated with important economic variables, such as the degree of liberalisation of air transport markets, and the extent of participation in international production networks (Arvis and Shepherd, 2011).

2.1.2. Connectivity at hub airports

From the perspective of an airport, the core function of a hub is not only reflected in the number of directly connected destinations, but also in its ability to provide transit connections as a central node. Thus, the level and quality of hub connectivity has long been a focus of research. Models developed in the literature include the consideration of degree centrality to measure the connectivity of U.S. hub airports (Shaw, 1993), the clustering coefficient to reflect the spatial location of hub airports in the network (Bagler, 2008), the shortest path length accessibility model (Malighetti et al., 2008), or the quickest path length accessibility model (Paleari et al., 2010).

However, measuring airport connectivity solely in terms of the number of connections between network nodes (or destinations w.r.t. air travel) does not take into account the differences in connection quality due to factors such as the degree of the detour, transit time, flight departure and arrival times, aircraft type, etc. Hence, further studies have begun to consider the quality of individual connections specifically from the perspective of passenger utility. For example, the NetScan connection unit approach and the Weighted Number of Connections (WNX) index construct connectivity indicators with factors of detour and transit time (Burghouwt and Wit, 2005; Burghouwt and Redondi, 2013). The Weighted Number of Feasible Connections (WNR) model determines the minimum connectivity index by the type of connecting flight based on the WNX approach (Zhang et al., 2019). The Hub Connectivity Index (HCI) was developed to measure the connectivity of hub airports from a temporal perspective, incorporating detour and transit time thresholds (Li et al., 2012). And the Airport Connectivity Quality Index (ACQI) was developed to represent the connectivity of direct and indirect connections based on the size of the destination airport (Wittman and Swelbar, 2013).

There is also literature that specifically examines the service capacity of hub airports from an international connectivity perspective. Danesi (2006) have analysed the transit connectivity of major European international airports using a continuous hub connectivity index. Huang and Wang (2017) found that Beijing Capital, Shanghai Pudong, Guangzhou Baiyun and Kunming Changshui airports have a more pronounced flight wave system based on a technical process of flight wave identification and a feeder route study methodology, which means more possible indirect connections. Zhu et al. (2018) measured the overall connectivity of 69 airports in China and major airports in Australia and concluded that the connectivity of Australian airports was higher than that of most airports in China.

2.1.3. Multi-modal connectivity

Zhu et al. (2019) proposed the Connectivity Utility Model which can be used to assess the connectivity of an airport, a train station, a city or a region in multi-modal transport networks. This model is built based on the Dynamic Weighted Model (Zhu et al., 2018) and the NetScan model (Burghouwt and Veldhuis, 2006). The dynamic weighted model proposed by Zhu et al. (2018) applied the Connectivity Utility Model to assess the terminal connectivity scores of airports and train stations within their selected urban areas, subsequently establishing rankings.

Notably, Nanjing Railway Station achieved the highest connectivity score among all railway stations, with a score of 61,501.4. However, this score is relatively low when compared to prominent airports such as Beijing Capital Airport (92,453.06), Pudong Airport (82,677.32), and Hong Kong Airport (75,951.37). This questions the appropriateness of such a direct comparative ranking.

In conclusion, firstly, early studies looked more at spatial connectivity and although later on the quality of connectivity was considered more, quality attributes were still discussed at a more superficial level, essentially focusing on destination importance or scale, flight frequency or seat capacity, transit connection times and quality of connections. Little literature explores deeper into more indicators to measure quality, such as on-time performance, international market proportion, or the distribution of departures and arrivals throughout the day. Secondly, except for a small number of studies exemplified by Matisziw and Grubesic (2010) and Meire et al. (2019), most of the existing connectivity measures are only constructed for the network of a single transport mode. Matisziw and Grubesic (2010) conducted an assessment of locational accessibility within the US air transportation system, which integrated ground access considerations to catchment airports and accessibility within the air network. Similarly, Meire et al. (2019) calculated bimodal accessibility in the context of Australia, factoring in both land- and airside accessibility components. However, many attributes of multi-modal transport have not been taken into consideration, such as the overlap of destinations, connection opportunities given the characteristics of the modal interchange, multi-modal transfer efficiency and ground access options. Thirdly, the categorization of factors for measuring connectivity lacks a universal standard approach. For instance, the airport's size is frequently utilized as a weight factor in indexed metrics, although it is also an indicator of capacity and can be classified as such. In addition, certain passenger utility indicators, such as connecting time and quality, should be considered in the context of a convenience indicator. This article argues that the breadth and depth of definition and measurement of connectivity research has much scope for expansion at both research and practical levels, and that indicators can be more rationally categorised according to their different characteristics.

3. Methodology and data

3.1. Assessment methodology

Previous studies on the assessment of multi-modal transport have generally used methods such as Data Envelopment Analysis (DEA) (Koohathongsumrit and Meethom, 2021; Swami and Parida, 2015), Analytic Hierarchy Process (AHP) (Ho, 2008; Lin et al., 2021), Fuzzy Comprehensive Evaluation (FCE) (Han et al., 2020), Principal Component Analysis (PCA), grey system evaluation (Kumar and Anbanandam, 2020; Wang, 2014) and factor analysis (Jiang and Shao, 2014). However, these methods have some extent of uncertainty in obtaining weights, and there are also certain difficulties in data processing due to the differing nature of the data for a large number of air-HSR assessment indicators. Fractal analysis is data-driven and relies on the inherent characteristics of the data points themselves to uncover patterns and behaviours without imposing subjective weightings, making it suitable for evaluating complex systems where the importance of indicators may dynamically vary based on their context and relationships. Fractal analysis operates on the principle of capturing the spatial distribution and relationships among indicators. Instead of assigning predetermined weights, it considers the self-similarity and interconnectivity of indicators in the assessment of the overall system (Benguigui, 2016; Nardo et al., 2018). By refraining from imposing predetermined weights, fractal analysis accommodates the adaptability required to evaluate systems with intricate interdependencies (Kim et al., 2007). A higher fractal dimension suggests greater complexity and variation, which could be interpreted as certain indicators playing a more influential role in shaping the system's spatial structure.

3.1.1. Fractal theory

The fractal theory is derived from fractal geometry, first introduced by French-American mathematician B.B. Mandelbrot in 1967 in his paper 'How Long Is the Coast of Britain?' A fractal is the shape of a complex system whose local structure is enlarged to resemble the whole in some way. The fractal theory assumes that everything that exists in nature has a diverse hierarchy of scales and that there is self-similarity between parts and the whole. Fractal geometry uses simple mathematical concepts as a starting point to express the complex and irregular forms of nature in a mathematical language, exploring the generative logic behind complex forms compared to Euclidean geometry (Nardo et al., 2018; Sreelekha et al., 2017).

Traditionally the dimensions of objects in Euclidean geometry are integer dimensions. Dimensionality can be used to characterise geometric objects. A point corresponds to zero dimension, a line corresponds to one dimension, a plane corresponds to two dimensions, and a cube corresponds to three dimensions. From the point of view of mathematics, if a D-dimensional geometric figure is expanded by a factor of r in all independent coordinates, N figures similar to the original result. By comparing the figures before and after the expansion, it can be concluded that the relationship between the number of similar figures produced and the multiplier of expansion follows the eq. $N = r^D$ (Wen and Cheong, 2021; Zhang et al., 2014). A larger fractal dimension (D) indicates that the figure fills more space. The formula in integer dimensions can be extended to non-integer dimensions. The new formula is obtained by performing logarithmic operations on each side of the above formula, i.e., $D = \log N/\log r$ (Fractals and the Fractal Dimension, 2022).

Fractal analysis is a nonlinear method that focuses on the relationships between the variables and how they contribute to the overall structure (He and Ge, 2020). It has been widely applied in mathematics, physics, biology, medicine, economics, management and other fields for the study of irregular and complex structures. Wen and Cheong (2021) found that most real-world networks exhibit self-similarity and have fractal dimensions. Gneiting et al. (2012) assessed the roughness of time series and spatial data with estimators of fractal dimension. Nardo et al. (2018) applied complex network and fractal theory to the assessment of water distribution network resilience to pipe failures. Zhao et al. (2021) used a hybrid approach of fractal theory, information value, and random forest models to assess the landslide susceptibility of a transmission line in Gansu Province, China. Fractal analysis has been conducted as an effective tool for quantitative assessment and representation of complex systems.

Air-HSR intermodal networks are inherently complex and interconnected systems. Fractal analysis excels in evaluating such systems where the relationships between indicators are intricate and may not follow a linear weighting scheme. The absence of explicit weights allows for a more adaptive approach, considering the interdependencies among indicators (Sreelekha et al., 2017).

3.2. Design of the assessment framework

System integration refers to a virtuous cycle in which sub-systems adapt to each other, collaborate and promote each other to achieve the overall optimum (Yu and Jiang, 2021). Drawing on the theory of the synergistic effect (Pezzani et al., 2019) and the connotation of integration, this paper considers that 'air-HSR network integration' refers to the collaborative development of air and HSR transport networks in the same region, according to their characteristics and strengths, in a way that ensures convenient transfer opportunities between both services, so that they constitute a whole integrated network with increased accessibility. A deliberate decision was made to adopt an airport-centric approach in the evaluation and analysis of air-HSR intermodal transport, with a specific focus on enhancing intermodal networks from the perspective of air transport stakeholders. This comes from the realisation that competitive forces normally favour HSR for shorter travel times, and thus airlines and airports tend to take the lead in offering passengers air-HSR services. Moreover, the global nature of air transport networks makes them more prone to consider connectivity beyond single providers, whereas train operators are normally concerned with networks that exhibit clearer geographical boundaries.

The appraisal of the degree of air-HSR network integration is essentially an assessment of the synergy and differentiation of air and HSR network connectivity and service capabilities. Due to the complexity of the air-HSR intermodal network, the indicators are interrelated and interact with each other, so the assessment framework should follow a hierarchical structure to capture such interaction. In this paper, the primary set of indicators focus on three aspects: service capability, network connectivity and transfer potential.

Service capability means the infrastructure provision and the ability to provide the integrated service, which is measured by indicators such as scale, daily delivery capacity, speed of HSR station, airport on-time performance as well as hub status in the network. We selected different indicators for airports and HSR stations based on their operational characteristics and data availability. During the data collection process, it transpired that the majority of the top 50 largest airports in China has reached their declared capacity in 2019, meaning the actual number of passengers was over the capacity, therefore the number of passengers can better represent the service capability and the size for airports. In contrast, there is no official public data on the annual passenger volume of each HSR station in China, thus other metrics that best represent the capacity of the HSR station are needed. Available tracks in HSR stations often limit the volume of trains that can be safely provided. Maximum daily passenger accounts for the passenger handling capability of a station. These two indicators together determine the service capacity and operational ceiling of the HSR station. The difference in metrics for each mode also reflects their operational characteristics. Owing to the security protocols enforced at airports, air travellers commonly experience prolonged wait times at the terminal. Conversely, HSR passengers can normally arrive at the station and board a train with minimal dwell time. Consequently, the actual passenger count at the airport serves as a tangible metric for assessing its service capacity, whereas it is difficult to reflect the essence of the situation by relying solely on the indicator of the actual number of HSR passengers.

Network connectivity means the ability to provide access to the destinations in each network and the degree of complementarity between the networks, which is measured by indicators such as the number of destinations, frequency, the coverage of catchments and the level of overlap in the sub-networks. Similarly, the choice of metrics aligns with the unique characteristics and passenger expectations of each mode of transportation. Under the context of air-HSR intermodal travel, air passengers would be more concerned with the variety of flights available, while rail passengers often prioritise service frequency for seamless connections. Correspondingly, the number of flights at airports emphases global connectivity and hub functionality, while the headway of trains at HSR stations highlights the importance of frequency and operational efficiency in rail travel.

Transfer potential reflects the ease and value of transfer between the HSR station and the airport (and vice versa), which is measured by indicators such as connection opportunities, ground transportation modes and transfer efficiency. According to the connotation of air-HSR network integration and the characteristics of the primary indicators, 16 secondary indicators have been set up to form a Network Integration Assessment Framework. Description of the indicators, calculation methods and data are shown in Table 1.

3.3. Model design

Drawing on the idea of network-covering algorithms and fuzzy sets fractal dimensional models(Zhang et al., 2014), the model proposed in this paper to assess intermodal integration is processed in three steps: Data standardisation, de-correlation and fractal assessment.

3.3.1. Standardisation

Due to the inherent complexity of the air-HSR network integration assessment framework, coupled with the different units of each indicator, it is not straightforward to compare each of them directly. In this case, the data can be pre-processed to obtain comparable scales and normalised values using the minimum or maximum value for each indicator in each air-HSR combination. The model denotes the j-th secondary indicator of the i-th air-HSR combination as A_{ij}.

$$A = \begin{bmatrix} A_1 \\ \vdots \\ A_m \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \tag{3.1}$$

The indicators in the matrix A are normalised with formula 3.2.

When a_{ij} is positive, $\acute{a}_{ij} = \frac{a_{ij}}{a_{maxj}} \times 100$; when a_{ij} is negative,

$$\acute{a}_{ij} = \frac{a_{ij}}{a_{minj}} \times 100 \tag{3.2}$$

Where a_{maxj} , a_{minj} are the maximum and minimum values of different air-HSR combinations at the j-th indicator attribute, respectively.

The pre-processed data are then standardized with formula 3.3.

$$b_{ij} = \acute{a}_{ij} - \frac{\overline{\acute{a}_j}}{s_j} \tag{3.3}$$

b_{ij} is the standardized data of $\acute{a}_{ij}$, $\overline{\acute{a}_j}$ is the mean of the unstandardised j-th indicator, and s_j is the standard deviation of the unstandardised j-th indicator.

$$\overline{\acute{a}_j} = \frac{1}{k}\sum_{i=1}^{k} \acute{a}_{ij} , \tag{3.4}$$

$$s_j = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}\left(\acute{a}_{ij} - \overline{\acute{a}_j}\right)^2} \tag{3.5}$$

3.3.2. De-correlation

B is a matrix of normalised secondary indicators b_{ij}. There is still correlation between the various indicators. In order to eliminate this relationship, it is necessary to find an $n \times n$ dimensional matrix P to transform B such that the indicators are de-correlated and transformed into C_{ij}:

$$C_{ij} = \left(C_{i_1}, C_{i_2}, \dots, C_{i_{n_i}}\right)^T = BP \tag{3.6}$$

Using multivariate statistics, we could calculate the covariance matrix M_{ij} of matrix B.

$$M_{n_i \times n_i} = \begin{bmatrix} cov(B_1, B_1) & \dots & cov(B_1, B_{n_i}) \\ \vdots & \ddots & \vdots \\ cov(B_{n_i}, B_1) & \dots & cov(B_{n_i}, B_{n_i}) \end{bmatrix} \tag{3.7}$$

$$cov\left(B_{n_i}, B_{n_j}\right) = \frac{\sum_{k=1}^{m}\left(B_{ik} - \overline{B_i}\right)\left(B_{jk} - \overline{B_j}\right)}{n-1} \tag{3.8}$$

In C_{ij}, the secondary indicators are uncorrelated to each other and contain all the information of the original secondary indicators. At this point, the transformed new secondary indicators are uncorrelated.

3.3.3. Fractal assessment

Consider a sphere of radius r with the origin in the centre of the N-dimensional space. All the indicators Cij can be contained within the sphere when $r = R = \max(Cij)$. The distance from each point to the origin is given as d_{ij}. To make sure all distance values are positive, if $C_{ij} < 0$, a value of $\delta = max\{|C_{ij}| , C_{ij} < 0\}$, is used to convert to $C_{ij} \Longrightarrow C_{ij} + \delta$, such that the N values of $C_{ij} \geq 0$.

Table 1
Air-HSR Network Integration Assessment Framework: Definition of primary and secondary indicators.

Primary indicators	Secondary indicators	Definition	Observations
Service capability	Airport size	The annual number of passengers departing and arriving at the airport by air.	Reflects the capacity of the airport to provide air services. Source: IATA (2019)
	Airport OTP	The percentage of flights that arrive and depart from an airport within a specified time frame, typically within 15 min of their scheduled arrival or departure time.	On-time performance, reflecting airport and airline operating efficiency and quality. Source: OAG (2022)
	HSR station size	The number of tracks available at the HSR station is used a proxy for its capacity as it relates to the number of trains it can receive in a given period of time.	The corresponding closest pair of HSR station-airport is chosen according to the distance by the fastest mode of surface transport. Source: China Statistical Yearbook (2021)
	HSR daily delivery capacity	Maximum number of passengers transported by high-speed rail in a single day.	Reflects the capacity of the train station to provide HSR services. Source: China Academy of Railway Sciences (2022)
	HSR Maximum speed	The upper limit of operating speed for the lines using the HSR station (km/h).	Reflects the expected quality of HSR services. Source: China Statistical Yearbook (2021)
	Proportion of transfer passengers at the airport	Transfer passengers as a percentage of total passengers.	Reflects airport transfer capacity and hub status. Source: IATA (2019)
	Proportion of international passengers at the airport	The proportion of international passengers to total passengers.	Reflects the structure of international and domestic routes and the level of international connections at the airport. Source: IATA (2019)
Network connectivity	Destinations available at the airport	Number of total different destination (cities).	Reflects the connectivity of domestic and international air networks. Source: IATA (2019)
	Number of flights per day at the airport	Total number of flights in 2019/365 days.	Reflects the service quality of the air network in terms of opportunities to travel by air. Source: IATA (2019)
	Distribution of flights (at the airport) throughout the day	Average time distribution (B) of flights to each destination in a day, seven days a week: $\mathrm{B} = \frac{1}{\mathrm{n}}\sum_{c=1}^{n}\left(\frac{1}{7}\sum_{j=1}^{7}\mu\lambda\right)$ Where n is the total number of destinations (c); j is the day of the week; μ denotes the availability of flights to the same destination in 4 segments of the day (00:00–05:59,06:00–11:59,12:00–17:59,18:00–23:59), i.e., if flights to a city c appear in 3 segments of the day, then $\mu = 3/4$; λ is the flight distribution considering 30 mins interval time segments (i.e., if the flights to a city c appear in 3 intervals, then $\lambda = 3/48$).	Reflects the distribution of flights to a particular destination throughout different time periods of the day. Source: OAG (2019)
	Number of stops on the HSR routes	The number of stations reachable within 800 km (about 3 h) of the HSR station.	Reflect the catchment opportunities for the HSR station. Source: 12306 China Railway (2019)
	Headway between HSR services	Average time duration (in minutes) between high-speed train arrivals at the HSR station during the day, by dividing the number of minutes in a day by the average number of trains arriving at the HSR station each day.	Reflects the availability of train connections throughout the day. 2019 data is used as some trains suspended operation due to the response to the Covid-19 pandemic. Source: 12306 China Railway (2019)
	Network overlapping	Coincidence coefficient between subnetworks: $\mathrm{D} = 2^*\lvert AA\cap BB\rvert/(\lvert \mathrm{A}\rvert + \lvert \mathrm{B}\rvert)$	$0 \leq \mathrm{D} \leq 1$. $\mathrm{D} = 0$ means that the markets accessible by air and rail are completely differentiated. $\mathrm{D} = 1$ means both networks provide access to the same markets. The larger the value of D, the higher the degree of overlapping. Sources: 12306 China Railway (2019); IATA (2019)
Transfer potential	Transfer opportunities	H * F Number of trains (H) arriving within a 2–4 h time window, times the number of flights (F) departing within the same time window.	Reflects the connection opportunities between flights and HSR trains 2019 data. Source: OAG (2019); 12,306 China Railway (2019)
	Transfer modal choice	Number of ground transportation options between the airport and HSR station.	Reflects the selection available between subway, airport shuttle, car, bus and other ground transportation options. Source: Gaode Map (2023)
	Transfer efficiency	The reciprocal of the average travel time from the HSR station to the airport using the fastest mode available. I.e., the average number of transfers that passengers could complete per hour.	Reflects the quality of the transfer alternatives between the airport and HSR station. Source: Gaode Map (2023)

Only when $r = R = max(C_{ij})$, the sphere contains exactly all the points N in it, then the number of points C(r) inside the sphere of radius r is denoted by:

$$C(r) = \sum_{i,j} H(r - d_{ij}) \tag{3.9}$$

Where H(x) is the Heaviside function:

$$H(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{3.10}$$

C(r) is a cumulative distribution function that reflects the distribution of indicator points in space. lnC(r)and lnr are linearly related, and the fractal dimension D is the slope of lnC(r)-lnr curve:

$$D = \frac{d(\ln C(r))}{d(\ln r)} \tag{3.11}$$

The actual scatter plot of lnC(r) -lnr is fitted to a straight line and the slope of the fitted line is used to replace the fractal dimension approximately. The fractal dimension (D) reflects the distribution of the indicator points in the space. Specifically, it measures how the number of indicator points changes as the distance between them changes. A larger fractal dimension indicates that the distribution of the indicator points is further away from the center of the sphere, implying that the points are more spread out and the space is more effective in accommodating complex forms. Thus, a higher value of the fractal dimension indicates a more effective use of space by the air-HSR complex network. From a geometric perspective, a higher value of the fractal dimension corresponds to a higher overall score of the indicators, highlighting the network's ability to occupy and utilise space in a complex and efficient manner. Therefore, by measuring the fractal dimension, we can assess the effectiveness of the air-HSR complex network in utilising space and accommodating complex forms.

3.4. Implementation in MATLAB

The model proposed for the fractal analysis was solved using MATLAB. More specifically, the *Z-score* function was used to standardise and normalise the original values for each indicator, the Cov and Eig functions to eliminate correlation, the Find and Index functions to solve for the maximum radius, and the For and Sum functions are used to determine the covariance matrix M(r). Then the value of r, lnr and lnM (r) can be calculated. Then, the integrated service level of the air-HSR combinations are assessed by calculating the fractal dimension of each of the three primary indicators.

3.4.1. Application to the Chinese multimodal network

The assessment framework defined previously can be used to evaluate the degree of the air-HSR network integration in different contexts. This paper focuses on cities as the geographical unit of analysis for an empirical application. The study starts with the selection of a sample of ten airport, comprising the six highest-ranking international hubs in terms of passenger numbers for the year 2019, as well as four airports positioned within the national ranking range of 10th to 20th for regional hubs in the same year, following the local definition of Civil Aviation Administration of China (CAAC, 2018), each with their corresponding nearest HSR stations, as shown in Table 2. This selection serves the purpose of facilitating meaningful comparisons. The largest HSR station in each city was not selected because, upon comparison, it was found that the closest HSR station to the airport in each city was an average distance of 18.3 km, while the largest HSR station was an average distance of 38.9 km from the airport (shown in Table 2). Long distances like these would hardly lead to seamless air-HSR intermodal opportunities. For the cities with multiple airports (Beijing, Shanghai and Chengdu), Capital Int'l Airport, Pudong Int'l Airport and Shuangliu Airport are selected, because the new airports in Beijing and Chengdu started operation in late 2019 and 2021 respectively, and Pudong airport is the primary international airport in Shanghai and ranked higher.

4. Results and analysis

Based on the algorithm described in Section 3.3, the fractal dimension associated with the primary indicators were calculated based on the corresponding secondary indicators, and the overall dimension for each city was derived from all the secondary indicators. Logarithmic scales are used to plot the data because the fractal dimension is a non-integer value, and this type of plot indirectly determines the fractal dimension by finding the slope of the line of best fit (for each city) in the log-log plot. The fractal dimension associated with the primary indicators were calculated based on the corresponding secondary indicators, and the overall dimension for each city was derived from all the secondary indicators. In Fig. 1 and Fig. 2, *lnM(r)* represents the logarithm of the number of spheres required to cover the fractal object for a given scale factor (r). It indicates the complexity of the fractal object at different scales. Whereas *lnr* represents the logarithm of the scale factor (r). It

Table 2
Airports and corresponding HSR stations selected for analysis.

City	Airport	IATA Code	Airport Type	Nearest HSR Station	Distance between the airport and the nearest HSR station (km)	Largest HSR Station	Distance between the airport and the largest HSR station (km)
Beijing	Capital Int'l Airport	PEK	International hub	Beijing North Railway Station	35	Beijing South Railway Station	47
Shanghai	Pudong Int'l Airport	PVG	International hub	Shanghai Railway Station	45	Shanghai Hongqiao Station	58
Guangzhou	Baiyun Int'l Airport	CAN	International hub	Guangzhou North Railway Station	15	Guangzhou South Railway Station	50
Shenzhen	Baoan Int'l Airport	SZX	International hub	Shenzhen Airport North Station	0	Shenzhen North Station	33
Kunming	Changshui Airport	KMG	International hub	Kunming South Railway Station	33	Kunming South Railway Station	33
Chengdu	Shuangliu Airport	CTU	International hub	Shuangliu Airport Station	0	Chengdu East Station	23
Zhengzhou	Xinzheng Airport	CGO	Regional hub	Xinzheng Airport High-Speed Railway Station	0	Zhengzhou East Station	51
Changsha	Huanghua Airport	CSX	Regional hub	Changsha South Railway Station	34	Changsha South Railway Station	34
Wuhan	Tianhe Airport	WUH	Regional hub	Hankou Station	21	Wuhan Station	41
Haikou	Meilan Airport	HAK	Regional hub	Meilan Station	0.2	Haikou East Station	19

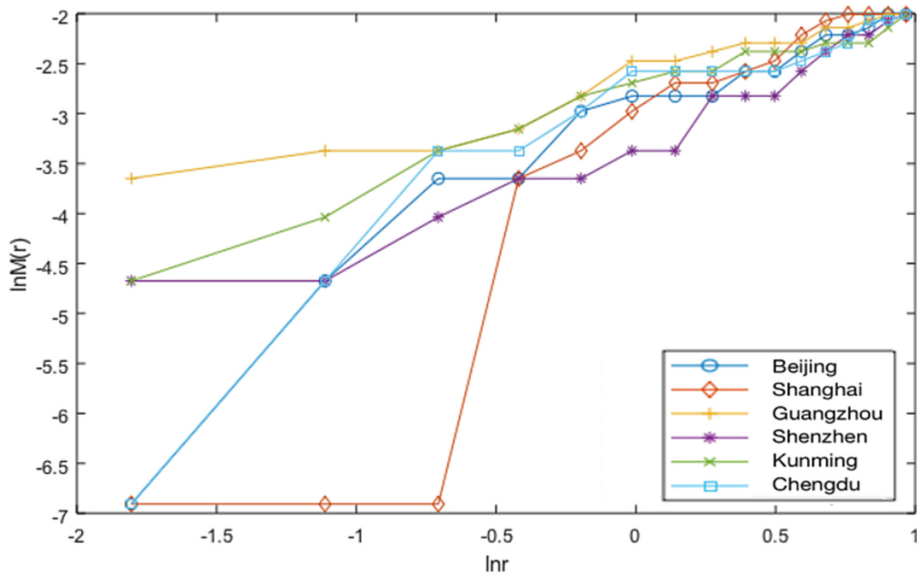

Fig. 1. Results for the assessment of secondary indicators in cities with international hub airports.

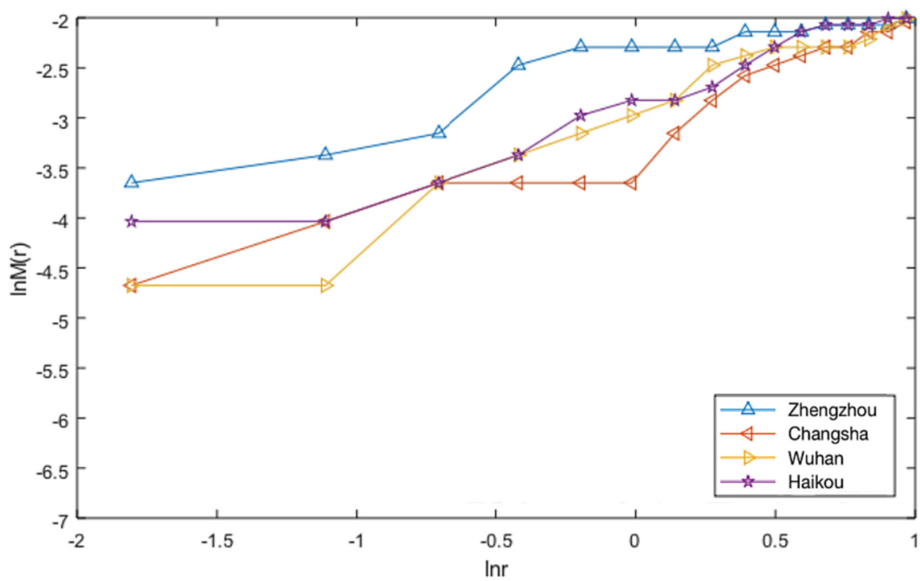

Fig. 2. Results for the assessment of secondary indicators in cities with regional hub airports.

indicates the size of the spheres used to cover the fractal object at different scales. A steeper slope, corresponding to a higher fractal dimension, reflects the fact that the scores for the indicators are more widely dispersed throughout the space. From a geometric perspective, a higher fractal dimension translates to a superior overall score for the network's performance indicators. This underscores the network's capacity to occupy space in an optimised and efficient manner, accommodating a range of complex configurations. A steeper slope and a higher fractal dimension indicate a network that excels in spatial integration and connectivity. Fig. 1 shows the results for cities with international hubs, Shanghai has the steepest slope, indicating the highest fractal dimension, while Guangzhou has the shallowest slope among the international hubs, indicating the lowest fractal dimension. Fig. 2 shows the results for cities with regional hubs, Wuhan has the steepest slope in the regional hubs but still much shallower than Shanghai and Beijing, meaning there is fairly large gap in overall integration level compared to the steepest international cities.

Considering the overall results, the fractal dimension for the entire assessment framework could be used to produce a ranking of the cities in terms of the degree of integration between air and HSR networks, as shown in Table 3. Shanghai ranks first with an overall score of 2.163, whereas Zhengzhou ranks 10th with an overall score of 0.615 despite having a HSR station located at the regional hub airport, suggesting that the presence of a HSR station at an airport or a HSR stop connecting the main station is not a determining factor in the level of network integration, especially when ground transfers are highly efficient or there are more modes for transfer. Both Chengdu and Shenzhen have HSR stations or stops at the corresponding international hub airports too and rank third and fourth, attributed to network connectivity and service capacity respectively, rather than transfer potential. Meilan station is also located within the premises of Haikou Meilan Int'l Airport and the city of Haikou ranks 8th overall, however, being located in Hainan Island, there are natural limitations to the coverage of the HSR connections.

Table 3
Ranking of Chinese cities according to the fractal dimension for the overall assessment of HSR-air network integration and the primary indicators.

Rank	City (airport – HSR station)	Service capability	Network connectivity	Transfer potential	Overall
1	Shanghai (PVG - Shanghai)	1.019	3.141	6.622	2.163
2	Beijing (PEK - Beijing North)	0.699	3.071	0.743	1.521
3	Chengdu (CTU - Shuangliu Airport)	0.885	3.320	0.891	1.463
4	Shenzhen (SZX- Shenzhen Airport North)	3.492	0.963	0.891	1.076
5	Wuhan (WUH – Hankou)	0.954	3.068	1.061	1.062
6	Changsha (CSX - Changsha South)	1.088	0.991	6.514	0.992
7	Kunming (KMG - Kunming South)	3.549	0.567	0.392	0.906
8	Haikou (HAK – Meilan)	1.019	1.016	1.061	0.886
9	Guangzhou (CAN - Guangzhou North)	1.145	0.673	6.622	0.668
10	Zhengzhou (CGO - Xinzheng Airport)	0.574	0.580	0.392	0.615

Overall, Shanghai, Beijing and Chengdu rank top three in comprehensive air-HSR network integration level. Shanghai ranking first overall is not a surprise, because it has the highest score in transfer potential (attributed to the wide range of transfer opportunities it offers, as well as the availability of multiple transfer mode options) and second highest score in network connectivity. But it only ranks fifth in service capability, mainly restricted by its lower airport on-time performance and lower HSR average speed. Beijing ranking second overall is mainly due to its good network connectivity in airport destinations, flight frequency and HSR catchment. But its performance in service capability and transfer potential is mediocre, which is particularly evident in HSR daily delivery capacity, average speed and ground transfer efficiency. Chengdu ranks third overall due to its excellent network connectivity, which demonstrates the importance of the feeding role of the HSR catchment. But Chengdu still has ample room for improvement in attracting air transfer passengers and optimising air-HSR connection opportunities.

From the perspective of the service capability indicators, Kunming, Shenzhen and Guangzhou rank top three. Kunming has the highest mainly because of its highest airport on-time performance, the largest scale of the HSR station and its fairly average high speed of HSR trains. Shenzhen ranks second mainly because it has the second highest airport on-time performance, the second highest airport international percentage and the second highest HSR daily delivery capacity. Guangzhou is also ranking high, which is because it has the highest percentage of transfer passengers at the airport, the second highest speed of HSR trains, the third highest airport on-time performance and third largest scale of HSR station. From these cases, it seems that the integrated service capability is not only closely related to the scale of the airport and HSR station, but also the service performance, including on-time performance and speed of trains, although the market distribution and hub status indicators like percentage of transfer and international passengers also play an important role.

From the perspective of network connectivity indicators, Chengdu, Shanghai and Beijing rank in the top three. Chengdu ranks first primarily because the fairly large number of stops on the HSR routes, which implies a large catchment of the hub, given that the station is located at the airport. Shanghai ranks second owing to having the highest distribution of flights throughout the day at the airport, as well as the second shortest average headway of HSR trains. Beijing ranks third due to the large number of destinations accessible from the airport with high flight frequency, as well as the comparatively low overlap of airport and HSR destinations. Based on these results, there is an indication that the focus of air-HSR network connectivity is not the same as the application of the concept in air-only networks. Besides the number of destination and frequency, the catchment, flight/train time distribution and the differentiation of destinations for each mode also play a critical role.

From the perspective of transfer potential, Shanghai, Guangzhou and Changsha rank top three. Our analysis reveals that the intermodal transfers between Pudong Airport and Shanghai Station exhibit lower efficiency, indicative of extended duration, yet compensate with an extensive array of connection possibilities, allowing travellers to access a wide range of destinations within an acceptable timeframe. Furthermore, this intermodal pairing demonstrates good performance in terms of ground transfer model options. These dual aspects jointly contribute to Shanghai achieving the highest rating in transfer potential, a distinction shared with Guangzhou. Shanghai boasts the maximum number of connection opportunities within the designated time window, while Guangzhou excels in offering a multitude of ground transfer alternatives. Changsha follows closely behind Shanghai and Guangzhou in overall rankings, with competitive strengths in connection opportunities, ground transport choices, and ground transfer efficiency.

5. Discussion and recommendation

The application of the model developed in this research shows that excellence in air-HSR network integration requires improvements in all the three areas. Service capability corresponds mainly to infrastructure supply, network connectivity corresponds to the provision of destinations and frequencies, and transfer potential corresponds to passenger transfer experience. If only service capability is available, the overall effect may be compromised by few intermodal connection opportunities, limited catchment and low connectivity destinations and quality. If the focus is only on network connectivity, connection opportunities and passenger experience may be compromised by capacity constraints and transfer efficiency. The air network, flight frequency and punctuality of the airport, the number of HSR lines passing through the city, the frequency and speed of HSR train operation, as well as the speed, variety and convenience of ground access, together determine the quality of integrated service and the range of passenger markets that an air-HSR hub can attract.

5.1. Service capability perspective

The analysis of results shown in the previous section establishes that two indicators, airport on-time performance and HSR maximum speed, play a more important role in the performance of the service capability indicators. Airport on-time performance is crucial for whether air-HSR passengers can connect to HSR trains at the expected time within the time window. Once a flight is delayed, passengers cannot complete their transfer within the planned time, thus affecting their later journeys and affecting other flights, which will greatly reduce the experience and choice of intermodal transport. In 2019, the average on-time rate of all airports in China was 81.65% (CAAC), and that of the airports in the 10 cities under closer analysis was only 79.6% on average. Shenzhen and Guangzhou rank high in service capability scores, in part because Shenzhen and Guangzhou boast 87.8% and 85% on-time rates respectively, which are much higher than other airports. China's HSR reports accurate on-time rates above 95% and even above 99% if a 10-min grace period is considered (China Academy of Railway Sciences, 2022). Therefore, the on-time performance of airports is the main issue that needs to be addressed when scheduling air-HSR connections.

HSR maximum speed is another key factor affecting the ranking of service capability. The main difference between HSR and other ground transport modes is its high speed and convenience, which is the main reason why it can compete with air transport. The attraction for travellers to choose air-HSR transport comes from the fact that it connects the airport with the final destination or origin in the shortest possible time. In five of the ten cases studied, the maximum speed of the HSR reaches or exceeds 300 km/h. Kunming, ranked first in the service capability indicator, and Guangzhou, ranked third, both have a maximum speed of 300 km/h.

5.2. Network connectivity perspective

From the network connectivity results, it is clear that network overlap and the number of stops on HSR routes are key indicators, which implies that efforts should be made to promote network differentiation and expand the coverage of HSR to improve overall connectivity. To maximise connectivity creation by leveraging their respective strengths, the air network could enhance international and long-haul routes, while the HSR focuses on surrounding and short-haul markets. By analysing the characteristics of overlapping destinations, routes with high repetition and low market demand should be cut. Vacant slots saved could be used for international flights. For overlapping destinations with great demand that cannot be eliminated, there is a need to coordinate flight and HSR schedules.

The number of stops on HSR routes is one of the necessary conditions for the success of air-HSR integration. The number of stops on HSR routes determines the accessibility and coverage of the network, and indirectly determines the market potential of the air-HSR option. If the coverage is limited, the HSR will only be able to bring a limited number of passengers to the airport, and the attractiveness of intermodal transport to passengers will be greatly reduced. In order to better connect the airport and the HSR service, the airport needs to strengthen its communication with the railway authorities and seek to establish additional airport stations or stops for routes that do not stop at the airport.

5.3. Transfer potential perspective

The optimisation of transfer efficiency is undeniably influenced by the geographical proximity of the airport to the largest HSR station in the city. The largest HSR station, characterised by an extensive network of service lines, higher frequencies, and a substantial catchment area, inherently fosters comprehensive connectivity within defined time windows. This proximity facilitates a seamless transfer experience between the airport and the station.

However, in the selected sample of 10 cities, the largest HSR station is situated at a considerable distance from the airport (38.9 km on average, as indicated in Table 2), posing challenges to the realisation of air-HSR intermodal opportunities. For instance, Guangzhou Baiyun Airport lies to the north of the city, while the largest station is positioned to the south. Similarly, Beijing Capital Airport is in the northeast, whereas the largest HSR station is in the south of the city. Chengdu Shuangliu Airport, located southwest of Chengdu, faces a similar situation, with the largest station situated to the east of the city. Only for Kunming and Changsha, the largest HSR stations are also the closest stations to the airport, albeit both being >30 km away.

Moreover, the nearest station (on average 18.3 km away from the airport) usually exhibits diminished network connectivity and service scale in comparison to the largest stations. This observation prompts a critical consideration for decision-makers in urban transport planning and development. It emphasises the necessity of devising strategies to enhance air-HSR intermodal transport, as an extensive distance between the airport and the HSR station post-construction can substantially curtail intermodal potential.

6. Conclusions

This paper presents conceptual innovations for network connectivity and integration, extends the breadth and depth of connectivity measurement research by creating new methods for calculating new indicators that have not been considered before and proposing the classification of connectivity indicators according to a formalised framework of assessment. By studying the current situation and problems of the air-HSR intermodal transport network in China, this paper proposes that it is necessary to conduct a comprehensive assessment of the integration of the air-HSR intermodal network. Based on a comprehensive literature review on network measurement and assessment methodology, an assessment framework comprising three primary indicators and 16 secondary indicators has been constructed – it is believed that this is the first attempt to achieve this in the transportation literature. Through analysing the advantages and disadvantages of various traditional assessment methods, the fractal theory was applied as a novel assessment method without the need for explicit weighting. The fractal dimension is used to describe the service capability, network connectivity, transfer potential and overall network integration level. This unique contribution assessment method can serve as an important complement to traditional methods and enrich the understanding of the complex spatial dynamics inherent in such networks.

Ten air-HSR combinations in Chinese cities were selected for an empirical application of both the framework and the model. The results show that most cities have wide variation between service capability, network connectivity and transfer potential indicators. Shanghai has the highest network integration level among the ten. It is also found that international hub airports together with their closest HSR station not necessarily perform at higher integration levels than regional hubs. The study concludes that excellence in air-HSR integration requires improvement in three areas, namely infrastructure supply, connectivity service and passenger experience. Based on the findings of the application case, the paper proposes reasonable policy and practical recommendations to enhance air-HSR network integration level from service supply, network coordination and transfer design perspectives.

Future research will continue to enrich and improve the assessment framework, and the study will be extended to all cities in China where both airports and HSR exist. With the aim of providing a more nuanced assessment of the unique attributes associated with each category, we intend to refine and analyse the assessment framework separately for international and regional airport hubs. Meanwhile, we will analyse the network topology of the selected cities, calculate macro-indicators such as complexity, connectivity and extensibility, and micro-indicators such as degree distribution and clustering coefficients, and compare their characteristics. As transport has not yet recovered under China's Covid-19 policy (as of 2022), the operational data in this paper uses observations from 2019, while the infrastructure data uses the latest 2022 data. The expectation is that consistent data will be used for further measurement once transport production has fully recovered for all modes. Alternative methods such as PCA or DEA could be employed alongside fractal analysis to provide a more comprehensive assessment. Along with the application of the comprehensive assessment method to other regional markets to make a side-by-side comparisons and analyse the reasons and differences to learn from experiences and practices in different contexts.

CRediT authorship contribution statement

Mengyuan Lu: Data curation, Methodology, Project administration, Writing – original draft. **Edgar Jimenez Perez:** Supervision, Writing – review & editing. **Keith Mason:** Supervision, Writing – review & editing. **Yin He:** Validation.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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