

A hierarchical spatial and temporal optimisation of the air-high speed rail intermodal network

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ARTICLE INFO

Keywords:

Air-high speed rail
Network optimisation
Spatial-temporal
Environmental impact

ABSTRACT

Spatial and temporal coordination of air-high speed rail (HSR) intermodal networks is important to reduce emission, improve service, enhance efficiency, and reduce costs in the provision of air-HSR integration. This paper constructs a hierarchical optimisation model that first considers a spatial scope to solve the problem of route allocation and frequency choice which minimises total environmental, operational and passenger cost with a Mixed-Integer Linear Programming (MILP) model, based on a demand estimation for passenger trips between city pairs. Then, the second hierarchical level of the model considers a temporal scope to maximise connection opportunities between the resulting air and HSR networks using time windows to adjust frequencies with a Prescriptive Integer Quadratic Programming (PIQP) model. An application to a network of 40 cities in mainland China with both air and HSR transport service shows that the total emission of the network can be reduced by 22 %. Comparative analyses show that optimising for passenger costs favours increased air travel on medium- and long-haul routes, while an emissions-focused approach encourages a shift toward HSR for short and medium distances. Sensitivity analyses on carbon pricing further highlight the potential of gradual price adjustments to incentivise lower-emission modes without requiring additional HSR infrastructure.

1. Introduction

Both air and high-speed rail (HSR) travel has grown rapidly in China since 2010, with passengers generally choosing air transport as their preferred mode of travel over long distances, and an increasing number of passengers preferring HSR for short and intermediate distances (Xia and Zhang, 2016). The two modes compete to varying degrees over a range of distances. Studies have shown that 900 km is the critical distance at which HSR effectively competes with airlines having a market advantage (Xu et al., 2016). In markets where HSR operates within 3 h travel time, HSR holds greater than 50 % of the market share. Moreover, the shorter the distance, the greater the market share HSR obtains (Xu et al., 2016). In the context of the rapid expansion of HSR networks worldwide, air-HSR intermodal transport has become an important means of relieving congestion at hub airports and reducing the environmental impact of transport (Zhu et al., 2018). At the same time, air-HSR intermodal transport can compensate for the loss of passenger traffic on short-haul routes and achieve the objective of attracting

passenger traffic (Zhu et al., 2019). Many countries around the world, such as France, Germany and China, consequently promote air-HSR intermodal transport. For example, Lufthansa and Deutsche Bahn expanded the air-HSR model into a whole network product covering 24 cities connected for Frankfurt Airport, advertised as Lufthansa Express Rail (Wandelt and Sun, 2022).

Nevertheless, air-HSR integrated operations are normally not considered at the beginning of planning and design, producing redundancy in the operation of their respective networks, inefficient occupation of hub capacity, and poor connections (Wang et al., 2020; Zhu et al., 2018, 2019). In China, 27 out of the top 50 airports by total passengers in 2019 had reached their declared capacity and a further 19 are close to saturation (China Academy of Railway Sciences, 2022). HSR stations in major cities also face congestion during peak hours and holiday periods. Moreover, the easing of China's travel policy in late 2022 after the Covid-19 pandemic, passenger numbers in airports and HSR stations are expected to resume rapid growth. Therefore, there may be an opportunity to rationally allocate air and HSR capacity to different

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<https://doi.org/10.1016/j.jtrangeo.2024.104085>

Received 21 June 2024; Received in revised form 28 November 2024; Accepted 28 November 2024

Available online 7 December 2024

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routes and optimise their frequencies to reduce inefficiency and emission, and at the same time coordinate timetables to facilitate passengers travelling by air-HSR intermodal transport. Therefore, the primary focus of this research is to explore the potential and benefits of cooperation between aviation and HSR across a national network. By examining how air and HSR services can complement each other on a larger scale, we aim to uncover ways in which integrated planning and resource allocation could enhance connectivity, optimise network efficiency, and support sustainable growth in intercity travel.

Spatial and temporal optimisation of the intermodal networks could promote effective integration of air-HSR transport. Intermodal optimisation is fundamentally about improving efficiency, or meeting the demand for inter-city mobility while minimising inefficiency and social costs, so that resources are allocated rationally and mismatches between supply and demand are reduced. This paper focuses on the network optimisation problem of air-HSR intermodal transport, three main issues are addressed: firstly, the estimation of inter-city flows, secondly, the efficient allocation of routes and frequencies of air and HSR services, and thirdly, the coordination of timetables for the maximisation of connecting opportunities. The optimisation model is designed primarily as a strategic framework that can guide collaborative efforts between stakeholders by identifying optimal routes, frequencies, and intermodal connections based on overarching network efficiency and demand objectives.

2. Literature review

The integration of air and HSR networks has been extensively studied, with a focus on understanding their interactions, optimising their networks, and improving coordination to enhance connectivity and sustainability. This review is structured to first provide an overview of the interactions between air and HSR modes, including competitive and cooperative relationships (Albalade et al., 2015; Xia and Zhang, 2016; Li et al., 2018), passenger preferences (Chen et al., 2024; Nurhidayat et al., 2023), and environmental impacts (Ruby and Clewlow, 2012; Jiang et al., 2021; Li et al., 2024). The subsequent sections delve into spatial optimisation strategies for air, HSR, and integrated air-HSR networks, exploring the use of advanced algorithms and models to enhance network efficiency (Aykin, 1994; Xu et al., 2016; Qianli et al., 2020; Sun et al., 2024). Finally, the review addresses the critical aspect of timetable coordination, emphasising methods to synchronise schedules for seamless intermodal transfers (Ke et al., 2020; Wang et al., 2021; Huan et al., 2023).

2.1. Overview of air-HSR intermodal transport

Albalade et al. (2015) studied the impact of high-speed rail transport on air transport in Europe and found that both competitive and cooperative interactions exist. Xia and Zhang (2016) analysed the impact of different transport distances on civil aviation and HSR transport and demonstrated that HSR has advantage over aviation for short distances and vice versa for long distances. As air transport tends to be limited by the capacity of a hub airport, air-HSR intermodal transport can take advantage of both modes only if it is well-coordinated at the temporal and spatial level. Sato and Chen (2018) carried out a feasibility study of air-HSR intermodal transport and proposed the method of using high-speed rail lines as feeder routes to the hub airport network for London Heathrow Airport. Li et al. (2018) used statistical theory to study the influencing factors of air-HSR cooperation and concluded that the distance between the airport and the HSR station was the key factor affecting both, and when the airport had a high-speed rail station, the two modes of transport achieved a seamless connection and the partnership between the two was significantly higher than when the airport does not have one. Wang et al. (2020) used a time window approach to examine the relationship between HSR and flights operating between city pairs, and their theoretical progress extended the field of study from

the spatial dimension to the spatial-temporal dimension. Yet, they explored the competing relationship between air and HSR and did not address the potential for network synergy and optimisation. Lu et al. (2024) established a novel assessment framework that considers service capability, network connectivity and transfer potential, and evaluated with fractal theory. However, this paper mainly focuses on evaluating the integration level of intermodal network rather than optimisation. Nurhidayat et al. (2023) provided a critical review of passenger preferences and the impact of HSR in the last 25 years. They found that the eight most commonly used attributes in mode choice models are the travel time, travel cost, frequency, distance, access time, population, GDP, access time and monthly level income. Chen et al. (2024) conducted a survey-based research, including travellers' concerns about travel security, comfort, convenience and reliability, and revealed that excessive concern for security and comfort among high-educated and high-income passengers with a low tolerance for transfer time would reduce the market share of air-rail service. Sun et al. (2024) evaluated the latest literature from 2019 to analyse six aspects regarding air / HSR interactions, including modal integration, modal competition, bi-directional impacts, emission aspects, robustness/ resilience perspectives, and proposed a set of ten challenging research questions, including considering more practical factors when related data is available.

Research on the environmental impacts of HSR on other modes of transport has seen an increase. Ruby and Clewlow (2012) examined the demand for HSR and aviation and their environmental impacts under alternative climate and energy policies in the USA. They found that energy savings and CO₂ emissions from HSR would increase substantially in combination with such policies. They also conducted an intercept survey in China and found that rail passengers tend to be more concerned about the environment than those individuals likely to choose air travel. Jiang et al. (2021) review the existing literature on the CO₂ emissions impacts of high-speed rail due to their interactions with aviation, roads and conventional rail. They divided the existing research into three levels, the first is a comparison of emissions between HSR and other modes, the second is the impact of HSR-induced traffic redistribution on emissions, and the third is life cycle assessment (LCA). Yao et al. (2022) developed a freight network model that combines node centrality, carbon emissions and time efficiency, and investigated the carbon reduction potential of an air-HSR intermodal express network compared to an aviation network. They found the proposed air-HSR network could provide express service nationwide in 24 h, while reducing carbon emissions by 2.08 million tons, or 57.35 % compared to the original airline network. Li et al. (2024) explored how the introduction of HSR in China has contributed to a reduction in aviation carbon dioxide emissions. They found that from 2010 to 2019, each city pair with an HSR connection has achieved cumulative savings of 69.57 thousand and 200.69 thousand tons respectively.

2.2. Spatial optimisation for air, HSR, and air-HSR integrated network

The literature on air network optimisation has mainly applied operations research modeling and algorithm solutions. Aykin (1994) was the first to investigate the problem of capacity-constrained hub network optimisation and used Lagrangian relaxation combined with branching bounding and heuristic algorithms to solve the model. Abdinnour-Helm and Venkataramanan (1998) studied the problem of designing hub networks without capacity constraints, developed a quadratic integer programming model and designed a genetic algorithm to solve it. Büdenbender et al. (2000) used a capacity-constrained air network model based on a time window to study a non-strict hub network, which was solved using a mixed-sum algorithm with taboo search and branching delimitation. Campbell et al. (2005) proposed a multi-allocation siting problem and used the network transport cost minimisation as the objective function, and the capacity of the hub airport and other factors as constraints. Camargo et al. (2009) considered the problem of how to design a multi-allocation hub network under

congestion at hub nodes, built a non-linear mixed-integer programming model and applied the Benders decomposition algorithm to solve it. Azizi et al. (2018) designed a multi-allocation-based hub network optimisation model with no capacity constraints, for each origin and destination node to select the shortest path as the transport path, but did not consider the capacity constraint of the hub airports. Sun et al. (2024) summarised based on the latest literature, that the optimisation problems focus on better aligning capacity with demand to ensure safe operations and achieve efficient allocation of increasingly scarce resources, including but are not limited to, schedule coordination, often achieved through slot allocation mechanisms, traffic flow management, aircraft sequencing, runway scheduling, and gate assignment. They have also mentioned that endeavours have been devoted to enhancing the capture of multiple objectives expressed by different stakeholders and proposing improved solution methods and algorithms that align with practical deployment requirements.

The literature on air-HSR intermodal network optimisation is scarce and normally based on original network designs. There does not seem to be any studies on quantitative optimisation improvements based on existing intermodal networks. Okumura and Tsukai (2007) applied genetic algorithms to find the optimal combination of Haneda Airport's capacity allocation to domestic destinations and the spatial configuration of the HSR network to maximise consumer surplus for domestic intercity passengers in Japan. Xu et al. (2016) built an air-HSR intermodal network model that allows direct flights, based on the P-hub problem research method of hub networks, with the minimisation of the total transport cost of the composite network as the objective function, and designs a traversal search-based shortest-circuit algorithm, specific paths were found with sample city data. By integrating node centrality, carbon emissions, and time efficiency into the model, Yao et al. (2022) developed an air-HSR express cargo network and analysed the carbon reduction potential. Qianli et al. (2020) analysed the structural characteristics and traffic radiation range of the Beijing-Tianjin-Hebei regional HSR network with a complex network and put forward qualitative optimisation directions based on the current network and existing planning.

2.3. Air-HSR timetable coordination

Coordinating timetables is a key factor in air-rail intermodal transport. Delahaye et al. (2022) found that the potential benefits of cooperation between air and rail have largely been studied, yet few timetable coordination methods have been proposed. Ke et al. (2020) formulated a multi-objective optimisation model, aiming at synchronising trains and flights at a specific airport by adjusting the railway timetable. The objective is to maximise the number of synchronisations and the coverage of synchronised flights, as well as to minimise the transfer penalties of passengers. However, the priority and time window settings for the three target equations had a significant impact on the results and schedule adjustments, with the original schedules requiring significant adjustments for different results. And the results show that passenger preference would be sacrificed when maximising the coverage of synchronised flights and the number of synchronisations, which means that the three objective functions could not reach consistency. Wang et al. (2021) proposed a model to improve service quality and enhance connectivity between the two modes by optimising HSR schedules. The model is set to maximise the number of connections between the two modes, considering whether the journey is 'air-rail' or 'rail-air' and dividing passengers into groups, the connection numbers improved by 40.2%. Delahaye et al. (2022) assumed that passenger discomfort is not due to change from the initial schedule, but that passengers have a preferred transfer time. In addition to rail schedules, they propose changes to the flight schedule to synchronise both ways. Tan et al. (2022) studied the HSR-Air schedule coordination (HATC) problem, which was solved by rearranging the HSR timetable to attract maximum HSR-Air traffic while considering minimal adjustments to the initial HSR

timetable. Jiang et al. (2022) proposed a method for optimising the Intercity High-Speed Rail (HSR) timetable based on dynamic passenger demand. An integer nonlinear programming (INLP) model is developed to minimise passenger waiting times, which also takes into account train capacity and saturation conditions. Huan et al. (2023) presented a practical methodology for improving seamless air-HSR intermodality by scheduling airline timetables and airfares, based on the intercity travellers' choice preference survey. They found that the percentage share of AHIS is at a low level of 3.31 % and 5.32 % in Beijing and Shijiazhuang, indicating that existing AHIS products are not yet sufficiently satisfactory.

In general, the existing literature on timetable coordination requires significant adjustments to existing flight and HSR schedules or a complete redesign to create maximum connection coverage and attract maximum passenger traffic. There is a lack of a method to maximise the connection opportunities between existing time windows of air and HSR, based on spatial allocation of air and HSR routes and slots using the existing schedules as a baseline.

While there is a considerable body of literature addressing demand forecasting, network optimisation, and the integration of HSR with air transport, there remain critical gaps in the comprehensive optimisation of air-HSR intermodal networks, particularly in combining both spatial and temporal dimensions. Existing studies have made progress in improving demand forecasting through the use of historical data, machine learning, and economic indicators, but these efforts are often limited to one mode of transport or lack holistic integration of air and HSR networks (Wandelt et al., 2024). Furthermore, although network optimisation is well-explored in both air and rail systems individually, few studies have effectively tackled the simultaneous optimisation of both spatial and temporal factors in the context of intermodal networks (Sun et al., 2024), leaving potential synergies between air and rail largely untapped. Additionally, while some works focus on operational efficiency and passenger transfer times in air-HSR systems, they often overlook the refinement of cost models, such as accurately calculating real operating and passenger time costs rather than relying on simplified metrics like fares.

The literature review suggests the need to comprehensively consider the optimisation of the air-HSR intermodal network in both spatial and temporal dimensions. This paper proposes to solve the optimisation problems by establishing a hierarchical multi-objective model to reduce redundancy, emission and costs, create more connection opportunities and improve the level of synergy between the two modes.

3. Methodology

3.1. Design of the model

A hierarchical procedure with multiple objectives was first proposed by Homburg (1998) for solving decision problems. His central idea is that the top level can provide general preference information from which weight restrictions are imposed, and the problem at the base level is to find a compromise that is consistent with the weight restrictions. Since then, the idea of hierarchical multi-objective decision-making has been applied in multiple fields. Fang et al. (2011) established hierarchical multi-objective equations to solve for the evacuation path of a stadium, involving three objectives to be achieved simultaneously, namely minimising the total evacuation time, minimising the total evacuation distance and minimising the cumulative congestion. And they devised an improved ant colony optimisation (ACO) algorithm to achieve this. Owais and Osman (2018) solved the bus network design problem with a hierarchical multi-objective genetic algorithm, using different coefficients to represent the relative importance of the objective function, which was solved by a two-layer programming model, an upper layer set up with a frequency decision model and a lower layer set up with a user path selection model. Xu et al. (2022) constructed a hierarchical optimisation model for distribution network planning,

integrated balancing network losses, line investments, power purchase costs, carbon emission costs and policy subsidies, and applied the NSGA-TS hybrid algorithm to the example analysis. Our approach draws on the essence of hierarchical optimisation, where the top level deals with broad specifications, and the lower-level deals with more discrete, specific goals. Moreover, we consider using higher level results as lower-level constraints.

Our model also draws on the ideas from the p -hub problem (the problem is to locate p hubs and to allocate non-hub nodes to hub nodes such that the maximum travel time or distance between any origin–destination pair is minimised, as proposed by Campbell et al. (2005)), the route planning and passenger allocation problem and the timetable formulation problem, splitting the problem into two hierarchies. In the first hierarchy, the main problem is to find a set of air and HSR routes and frequencies that minimise the operational cost, emission cost and passenger cost (time cost and monetary cost) while simultaneously satisfying the system's constraints, such as meeting the estimated demands for segments, number of aircraft/trains available and airport/train station capacities. Following this step, we should be able to know whether each route is operated by an air service or a high-speed train service or have both air and HSR services. Furthermore, the model could establish the frequency of each transport mode, as well as the number of passengers assigned to each mode. Therefore, we could also establish which cities are optimally selected as air-HSR hubs.

In the second hierarchy, the hubs obtained are examined in detail to focus on their timetables. The problem in this step is to find the schedule adjustment that enables the maximum air-HSR connections at the hubs, subject to existing timetable slots, flow balance and the total number of flight/train frequency adjustment assigned to each node. After this step, we would know which flights/trains need to be added or cut at which time slots during the day to maximise the connecting opportunities between the airport and the HSR station, combining with the number of frequencies allocated to each route in the first step.

3.1.1. Hierarchy 1 – Optimal route and frequency

The objective function of the top-level hierarchy (1) aims to minimise the passenger cost (time cost and monetary cost), emission cost and the operational cost of flights and HSR services in each route (See Table 1 for the symbols used in this hierarchy and section 4.2.1. for the definition of the parameters used in the application case).

Table 1
Nomenclature for hierarchy 1.

Inputs	Description
$C(N, R)$	N represents the set of city nodes and R represents the set of directional routes ($a - c$, city a to city c).
$Price_{air}^{a-c}$	Flight ticket price for route $a - c$.
$Price_{rail}^{a-c}$	HSR ticket price for route $a - c$.
$Time_{air}^{a-c}$	Time cost for a passenger travelling through route $a - c$ (directional) by air.
$Time_{rail}^{a-c}$	Time cost for a passenger travelling through route $a - c$ (directional) by HSR.
$Operate_{air}^{a-c}$	Flight cost of operating route $a - c$.
$Operate_{rail}^{a-c}$	High-speed train cost of operating route $a - c$.
$Emission_{air}^{a-c}$	Carbon emission of the flight operating route $a - c$.
$Emission_{rail}^{pk}$	Carbon emission of the HSR train operating per passenger kilometre.
$Distance_{rail}^{a-c}$	Mileage of the HSR train operating route $a - c$.
e	Carbon price per tonne.
$Demand_{a-c}$	Total passenger demand on route $a - c$.
$Available_{air}$	Total number of flights available.
$Available_{rail}$	Total number of high-speed trains available.
$Seat_{air}$	Seat capacity of each flight.
$Seat_{rail}$	Seat capacity of each train.
$Capacity_{air}^a$	Airport capacity, the maximum number of flights that the airport in city a can manage per day.
$Capacity_{rail}^a$	HSR station capacity, the maximum number of trains that the station in city a can manage per day.

$$\begin{aligned} \text{Min} \sum_{a,c \in C} & \left[(Price_{air}^{a-c} X_{air}^{a-c} + Price_{rail}^{a-c} X_{rail}^{a-c}) + (Time_{air}^{a-c} X_{air}^{a-c} + Time_{rail}^{a-c} X_{rail}^{a-c}) \right. \\ & + (Operate_{air}^{a-c} F_{air}^{a-c} + Operate_{rail}^{a-c} F_{rail}^{a-c}) + e \left(Emission_{air}^{a-c} F_{air}^{a-c} \right. \\ & \left. \left. + Emission_{rail}^{pk} Distance_{rail}^{a-c} X_{rail}^{a-c} \right) \right] \end{aligned} \quad (1)$$

As mentioned before, the intention of the hierarchy is to determine the routes and frequencies of the air and HSR network among the 40 cities on the spatial level. The cost-minimum reallocation of route and frequency in this step is subject to the inter-city passenger demand and the capacities, timetable connection will be considered in the second hierarchy.

Decision variables:

X_{air}^{a-c} : number of air passengers assigned on route $a - c$.

X_{rail}^{a-c} : number of HSR passengers assigned on route $a - c$.

F_{air}^{a-c} : number of flights assigned to route $a - c$.

F_{rail}^{a-c} : number of high-speed trains assigned to route $a - c$.

The minimisation problem is subject to the following constraints. Constraint (2) guarantees that the sum of the number of passengers allocated to air plus the number of passengers allocated to HSR in route k equals the number of total passengers in demand. Constraint (3) forces the sum of the number of air seats and the number of HSR seats to be greater than the number of passengers in demand. Constraint (4) ensures the flights allocated to each route do not exceed the airport capacity of departure city a or arrival city c . Constraint (5) ensures the trains allocated to each route do not exceed the HSR station capacity of departure city i or arrival city j . Constraint (6) limits the number of flights/trains in total. Constraint (7) restricts the value of decision variables to non-negative integer numbers.

$$X_{air}^{a-c} + X_{rail}^{a-c} = Demand_{a-c}, \forall a, c \in C \quad (2)$$

$$Seat_{air} F_{air}^{a-c} \geq X_{air}^{a-c}, Seat_{rail} F_{rail}^{a-c} \geq X_{rail}^{a-c}, \forall a, c \in C \quad (3)$$

$$\sum_{a,c \in C} F_{air}^{a-c} \leq Capacity_{air}^a, \sum_{a,c \in C} F_{rail}^{a-c} \leq Capacity_{rail}^c, \forall a, c \in C \quad (4)$$

$$\sum_{a,c \in C} F_{rail}^{a-c} \leq Capacity_{rail}^a, \sum_{a,c \in C} F_{rail}^{a-c} \leq Capacity_{rail}^c, \forall a, c \in C \quad (5)$$

$$\sum_{a,c \in C} F_{air} \leq Available_{air}, \sum_{a,c \in C} F_{rail} \leq Available_{rail}, \forall a, c \in C \quad (6)$$

$$\forall X_{air}^{a-c}, X_{rail}^{a-c}, F_{air}^{a-c}, F_{rail}^{a-c} \in \mathbb{N}^+ \quad (7)$$

3.1.2. Hierarchy 2 – Optimal intermodal scheduling

In hierarchy 2, we focus on the transfer opportunities at multi-modal nodes, i.e., the cases where the optimisation from hierarchy 1 suggests both air and HSR services are kept. This hierarchy is applied at node level, hence the schedule adjustment is suggested that maximises intermodal connecting opportunities at the node city. The rationale for this comes from the assumption that decision makers for the second hierarchy are concerned with the operational setting of the airport/train station in the city (for instance, a regional planning authority), that would define the specific trains/flights to adjust according to the slot allocation outcome of hierarchy 2. The objective function of the secondary-level hierarchy (8), thus, aims to maximise air-HSR connections at a given air-HSR intermodal node found in hierarchy 1, with flights/trains schedule adjustment in each time window (See Table 2 for the symbols used in this hierarchy and section 4.2.2. for the definition of the parameters used in the application case).

As mentioned before, the intention of the hierarchy is to determine the flight and HSR train schedule adjustment in each time window to

Table 2

Nomenclature for hierarchy 2.

$$\text{Max} \sum_{c \in C} \sum_{t \in T} \left[\left(\text{Frequency}_{air}^{c-a,t} + X_{air}^{c-a,t} \right) \times \left(\text{Frequency}_{rail}^{a-c,t+Transfer_{air-rail}} + X_{rail}^{a-c,t+Transfer_{air-rail}} \right) + \left(\text{Frequency}_{rail}^{c-a,t} + X_{rail}^{c-a,t} \right) \times \left(\text{Frequency}_{air}^{a-c,t+Transfer_{rail-air}} + X_{air}^{a-c,t+Transfer_{rail-air}} \right) \right] \quad (8)$$

Variables	Description
$C(N, R)$	N represents the set of city nodes and R represents the set of directional routes ($a - c$, city a to city c).
T	The set of time windows from 6:00 to 24:00 in a day.
$\text{Frequency}_{air}^{a-c,t}$	Initial frequency of flight from city a to city c from the airport at time t (every 10 min).
$\text{Frequency}_{rail}^{a-c,t}$	Initial frequency of HSR train from city a to city c from the station at time t (every 10 min).
Capacity_{air}^a	Airport capacity, the maximum number of flights that the airport in city a can manage per time window.
Capacity_{rail}^a	HSR station capacity, the maximum number of trains that the station in city a can manage per time window.
$\text{Transfer}_{air-rail}^a$	Transfer time needed from the airport to the rail station in city a .
$\text{Transfer}_{rail-air}^a$	Transfer time needed from the rail station to the airport in city a .
Add_{air}^{a-c}	Number of frequencies to be added/cut from the airport of city a to city c . (Negative number means cut frequency)
Add_{rail}^{a-c}	Number of frequencies to be added/cut from the rail station of city a to city c . (Negative number means cut frequency)

maximise the intermodal connections. The objective function (8) implies maximising the air-HSR connection, by adding or subtracting frequencies from the existing schedule¹ such that the product of the number of arriving HSR trains in time window t multiplied by the number of departing flights in the time window ($t + \text{Transfer}_{rail-air}$), and vice versa, is maximised. Therefore, the following decision variables are set:

$X_{air}^{a-c,t}$: Binary variable indicating whether there is flight added/cut from the airport in city a to city c in time window t .

$X_{air}^{c-a,t}$: Binary variable indicating whether there is flight added/cut from the airport in city c to city a in time window t .

$X_{rail}^{a-c,t}$: Binary variable indicating whether there is train added/cut from the station in city a to city c in time window t .

$X_{rail}^{c-a,t}$: Binary variable indicating whether there is train added/cut from the station in city c to city a in time window t .

Consider Fig. 1 to understand the effect of the objective function maximising connection opportunities. If the time window t is set to 10 min,² and the required transfer time Transfer in this city is 1 h, passengers of the single HSR train arriving between 08:00 am and 08:10 am to the train station in city a could transfer to the two flights departing between 09:00 am and 09:10 am from the airport in city a ; and vice versa, passengers on flights arriving between 08:00 am and 08:10 am could connect to the two HSR trains departing between 09:00 am and 09:10 am, but there are no flights scheduled to arrive at the airport in that time window. Then, the connection opportunities in city a for high-speed trains and flights arriving between 08:00 am and 08:10 am can be expressed as:

$$\text{Frequency}_{rail}^{c-a,0800-0810} \text{Frequency}_{air}^{a-c,0900-0910} + \text{Frequency}_{air}^{c-a,0800-0810} \text{Frequency}_{rail}^{a-c,0900-0910} = 1 \times 2 + 0 \times 2 = 2.$$

The frequencies assigned in hierarchy 1 are set as the constraints of this step. Constraint (9) ensures that the sum of frequencies at each time slot does not exceed the capacity for both the airport and the rail station. Constraint (10) ensures that the sum of frequencies at each time slot equal to the total added frequencies for both the airport and the rail station. Constraint (11) ensures that frequencies are non-negative. Constraint (12) ensures that the decision variables are binary.

$$\begin{aligned} \sum_{c \in C} \left(F_{airport}^{a-c,t} + X_{airport}^{a-c,t} + F_{airport}^{c-a,t} + X_{airport}^{c-a,t} \right) \\ \leq \text{Capacity}_{airport}^a \sum_{c \in C} \left(F_{rail}^{a-c,t} + X_{rail}^{a-c,t} + F_{rail}^{c-a,t} + X_{rail}^{c-a,t} \right) \leq \text{Capacity}_{rail}^a, \forall t \in T \end{aligned} \quad (9)$$

$$\begin{aligned} \sum_{t \in T} X_{airport}^{a-c,t} = \text{Add}_{airport}^{a-c}, \sum_{t \in T} X_{airport}^{c-a,t} = \text{Add}_{airport}^{c-a}, \sum_{t \in T} X_{rail}^{a-c,t} = \text{Add}_{rail}^{a-c}, \sum_{t \in T} X_{rail}^{c-a,t} \\ = \text{Add}_{rail}^{c-a}, \forall c \in C \end{aligned} \quad (10)$$

$$\begin{aligned} F_{airport}^{a-c,t} + X_{airport}^{a-c,t} \geq 0, F_{airport}^{c-a,t} + X_{airport}^{c-a,t} \geq 0, F_{rail}^{a-c,t} + X_{rail}^{a-c,t} \geq 0, F_{rail}^{c-a,t} + X_{rail}^{c-a,t} \\ \geq 0, \forall c \in C \end{aligned} \quad (11)$$

$$X_{airport}^{a-c,t}, X_{airport}^{c-a,t}, X_{rail}^{a-c,t}, X_{rail}^{c-a,t} \in \{-1, 0, 1\}, \forall t \in T, \forall a, c \in C \quad (12)$$

3.1.3. Feedback loop between the second and first hierarchies

The optimisation process reflects a dynamic feedback loop between the second and first hierarchies of the model. Any changes in connectivity arising from the optimisation of the second model (focused on maximising connection opportunities) would directly influence key parameters in the first hierarchy, such as demand, supply, and pricing. For instance, an increase in connection opportunities could raise demand, prompting adjustments in supply and price. Conversely, a reduction in connectivity could stabilise or lower demand, leading to further adjustments in the network's resource allocation.

Following the optimisation of air-HSR connection opportunities, two potential outcomes will emerge: (1) an increase in connection opportunities may enhance the attractiveness of the optimised city for passenger travel and transfers, or (2) a reduction in the frequency of both air and HSR services may occur. In the latter case, the goal is to retain and establish as many connection opportunities as possible to safeguard the network's connectivity despite reduced service frequency.

In the Connectivity Growth Scenario, demand within a city is expected to increase in proportion to the available connectivity opportunities. However, a cap on demand growth, such as a 10 % increase, should be imposed. While improved intermodal connectivity can stimulate travel demand, overall demand remains influenced by broader factors such as economic activity, population size, and city-specific characteristics. Consequently, connectivity improvements alone have a limited effect on demand growth. As demand rises, supply parameters—such as service frequency and pricing—respond cyclically. For instance, if demand increases in line with available capacity (i.e., seat availability), prices will remain stable. However, if capacity does not expand alongside demand, the increase will lead to higher prices due to the limited availability of seats.

¹ Historical timetables for services between the cities selected in hierarchy 1 are obtained for a representative weekday of 2019 from OAG (2022) and 12,306 China Railway (2022).

² On the one hand, no flights or trains with the same destination in every 10-min interval in the selected cases; on the other hand, 10-min window allows a balance between operational efficiency and flexibility for passengers and service providers, since it is short enough to maintain a tight schedule and high efficiency but also provides a buffer for minor delays and variability in passenger processing times. Managers may adjust to their airport and station schedules and actual operations.

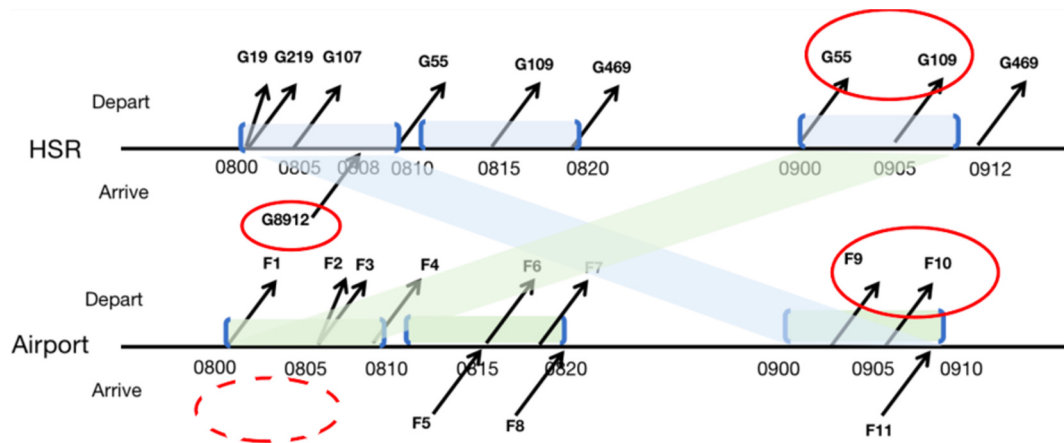


Fig. 1. Illustration of connecting opportunities in a given time window for passengers in HSR and air services in city *a*.

Given the capacity constraints that many cities in our study face, due to the airport capacity constraints, pricing is expected to adjust more flexibly than capacity. Airlines, in particular, can alter fares in response to changing demand more readily than they can expand seat capacity. Therefore, in cities where enhanced air-HSR connectivity increases travel opportunities, our model adjusts fares in proportion to demand growth, thereby maintaining a cyclical balance between demand, supply, and pricing.

Conversely, if the optimisation results in reduced service frequencies within a city, the network will focus on maximising transfer connection opportunities to meet existing demand. In this scenario, the optimised network prioritises connectivity by enabling as many transfer connections as possible, thereby ensuring that reduced service frequencies do not compromise the overall accessibility and connectivity of the network.

4. Empirical study

4.1. Context

In the context of China's growing transportation infrastructure and the increasing demand for connectivity within its domestic market, we identified a total of 43 cities across China (in 2022) that possessed both HSR and air services and where the main airport and station were mutually accessible in a reasonable time (see Fig. 2). 40 of these cities are situated on the mainland, while the remaining three were located on Hainan Island. These 43 cities play a crucial role in facilitating the

movement of goods and people, thereby contributing significantly to the economic development of their respective regions and the nation as a whole. As the three cities on Hainan Island are connected to each other by HSR, but not to the mainland, they were excluded from the analysis. Consequently, our investigation concentrated on the 40 mainland cities, which served as the focal points for the application of the spatial and temporal optimisation model outlined in the preceding sections. Before the optimisation process, the transportation network between the 40 cities has 623 directional routes where both air and HSR services coexisted; the number of routes where only one mode of transport is available, either air or HSR, is 818; and 484 routes are not served by air or HSR, but only by regular trains or buses.

The estimation of passenger demand between cities is a pivotal aspect of the empirical study, as we need to consider aggregated demand for air and HSR services. The estimation method we used integrates multiple factors to ensure accuracy and relevance (see equation below). Firstly, we employ data on the resident population of the originating city from China Statistical Yearbook (2022), recognising that population dynamics play a crucial role in shaping travel patterns. Additionally, we incorporate Baidu Mobility data (Baidu Mobility Database, 2019), which provides invaluable insights into the inter-city population travel mobility index in China by capturing city characteristics, distance, and economic activity interaction, pre-COVID-19, offering a real reflection of how people move between cities (Harvard Dataverse, 2020). To comprehensively capture the complexity of passenger demand, our analysis takes into account the proportion of daily out-of-town trips originating from each city. This parameter serves as a critical



Fig. 2. Cities in China with both airports and HSR stations.

determinant of travel demand, as it reflects the propensity of residents to embark on journeys beyond their permanent residences. Our approach encompasses both origin-destination and transfer passengers, acknowledging the intricate nature of inter-city travel, which often involves connections and transit between cities. Regarding the air and HSR ratio, data from the 2024 Inter-city Travel Industry Market Survey shows that train travel accounts for 60 %, road travel for 30 %, and air travel for 10 % of total inter-city trips (China Industry Research, 2024). A 2014 survey (no more recent data was available) indicates that of train trips, bullet train (speed between 200 and 250 km/h) accounted for 32 %, HSR (speed between 250 and 350 km/h) for 25 %, and conventional rail (speed below 160 km/h) for 43 % (World Bank Beijing, 2014). Considering the rapid expansion of China's HSR network and the rapid growth in capacity over the past decade, we estimate that the current total share of HSR and bullet train can reach 60 %–70 %, i.e., 36 %–42 % of the combined trips ($60 \% \times 60 \% = 36 \%$, $60 \% \times 70 \% = 42 \%$), and together with the 10 % of the trips accounted for by planes, we estimate that the total share of air plus HSR (including both high-speed rail and bullet train) is around 50 %. Additionally, we have now incorporated this estimate with a $\pm 10 \%$ adjustment based on city-specific factors, particularly resident income, given that higher incomes correlate with higher use of HSR and air travel (due to faster speeds and higher ticket prices). For example, in Shanghai—where resident incomes are among the highest in China—we estimate air and HSR travel share at 60 %. Lastly, in order to validate the accuracy of our passenger demand estimates, we leverage the OAG schedule segment seat data for the year 2019. If the number of estimated air and HSR trips is less than the number of flight seats between the two cities in 2019 from OAG, the demand for travel between the two cities is reassessed separately. By inspection, there were no instances where the inter-city demand calculated through the above methodology was less than the number of flight seats in 2019. This dataset serves as a benchmark against which our estimations are rigorously assessed, ensuring the robustness and reliability of our estimated data. The results of travel demand estimates are shown in Fig. 3.

$Combined\ demand(i-j) = population\ of\ the\ city\ i \times Baidu\ Migration\ index(i-j) \times proportion\ of\ average\ daily\ outgoing\ trips\ of\ the\ city\ i \times proportion\ of\ air$

$/HSR\ trips\ of\ the\ city\ i(50\% \pm 10\%)$

4.2. Data and assumptions

4.2.1. Parameters for hierarchy 1

The parameters for the first hierarchy outlined below have been selected to represent the operational dynamics and efficiency of the transport network in China, driven by specific data sources and calculations that are vital to understanding the intricate workings of the system. The ensuing numbered list delineates these parameters, elucidating their rationale and data sources.

- 1) Flight emissions: Emissions (tonne/flight) for each city pair is retrieved from ICAO CORSIA CO₂ Estimation and Reporting Tool (CERT) (2022) based on the flying distance. For aircraft type, based on data from OAG (2023), the most frequently used aircraft type on domestic routes in 2019, Boeing 737–800, was used. This aircraft type also had the largest seat share for the year, making it a representative for the calculations.
- 2) HSR train emissions: The average carbon emission of the HSR train operating per passenger kilometre is 0.00004 t/rpk (Jiang et al., 2021). The total HSR operating emission is calculated by multiplying unit emission (0.00004 t/rpk) with mileage between city pair and passengers assigned to the HSR for that city pair.
- 3) Emission cost: The carbon price of China's national ETS currently hovers at around 60 yuan (\$8) per tonne (Dialogue Earth, 2023). The emission cost is multiplied by the carbon price in China (60 yuan/t) with the emissions for each city pair by each mode.
- 4) Seat capacity of each flight: For domestic air travel, the aircraft type with the highest number of domestic flights and seats in China in 2019, after calculating with OAG data, is the Boeing 737–800. The average number of seats (170 seats) of this aircraft type in China in 2019 was chosen to represent the average seat capacity. Meanwhile, average flight load factor in China in 2019 is 83.2 % (CAAC, 2023).
- 5) Flight fare: Flight ticket fare for each city pair is retrieved from OAG for 2019 (2023). The historical annual average ticket prices

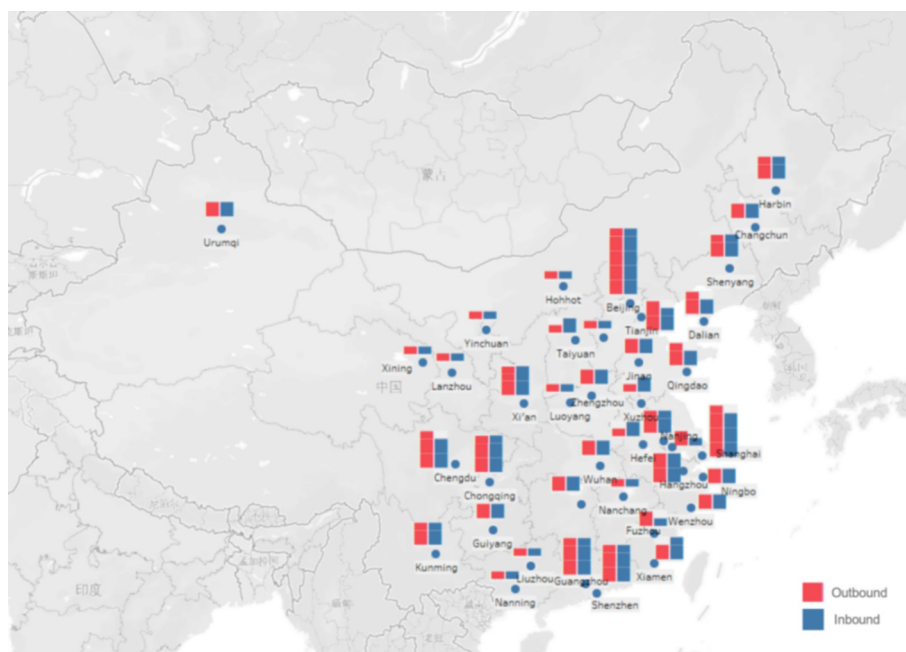


Fig. 3. Estimated outbound and inbound air and HSR intercity trips per day.

reflect real values and factors such as demand, competition, and distance, providing a realistic representation of current pricing strategies used by airlines. Besides, the average fare reflects the mix of traveller types and their respective pricing. For example, according to [CARNOC \(2021\)](#), the proportions of business, leisure, and student passengers in the air-HSR market are 15 %, 73 %, and 12 %, respectively. If we assume the pricing for a segment for each group is ¥300 for business, ¥200 for leisure, and ¥100 for students, the average fare we retrieved for this route would be: $¥300 \times 15\% + ¥200 \times 73\% + ¥100 \times 12\% = ¥203$

- 6) HSR fare: HSR ticket fare for each city pair is retrieved from 12,306 China Railway for 2019 (2023). The historical fares of the HSR reflect that the principle of diminishing distance is followed, i.e. the longer the mileage, the lower the average fare rate.
- 7) Seat capacity of each HSR train: the eight-car high-speed train in China has an average seat capacity of 600 ([China Academy of Railway Sciences, 2022](#)), which is used as the average seat capacity.
- 8) Cost of operating route k per flight: the average hourly cost for B737–800 in China in 2019 is 37,300 yuan/block hour (USD 5117/block hour) from [China Civil Aviation Annual Report, 2019](#), which is used as the average hourly flight cost. This figure is multiplied by the operating hours of each route from [OAG \(2023\)](#) for the flight route operating cost.
- 9) Cost of operating route k per HSR train: the average hourly cost for an HSR train in China in 2019 is 20 thousand yuan/h (USD 2744/h) from [China Railway Statistical Yearbook \(2022\)](#), this figure is multiplied by the operating hours of each route from 12,306 China Railway (2019) for the HSR route operating cost.
- 10) Passenger time cost on route k by flight/train: it is researched by Li et al. (2020) found via Logit model that the average value of air-HSR passenger time in China is 71.28 yuan/h. Specifically, business passengers account for 15 %, with an average time value of 124.6 yuan/h; leisure passengers account for 73 %, with an average time value of 81.29 yuan/h; student passengers account for 12 %, with an average time value of 44.69 yuan/h. These time values are multiplied by travel time on each route by flight and HSR train respectively for the passenger travel time cost. The different passenger proportions are used for estimating different passenger numbers. For example, if the daily travel demand for Beijing-Shanghai is estimated to be 17,996 passengers, the breakdown would be: business - 2699 passengers (15 %); leisure - 13,137 passengers (73 %); student - 2160 passengers (12 %).
- 11) Number of flights available: the total number of daily flight frequencies in the selected cities in 2019 is 9084, accounting for 75 % of the total flights in China's domestic air market. The data is captured from the OAG schedule database (OAG, 2022).
- 12) Number of HSR trains available: the total number of HSR trains in the selected cities in 2019 is 30,550, accounting for 72 % of the total in China's HSR market. The data is captured from 12,306 China Railway (2019).
- 13) Flight capacity of the airport: this means the maximum number of flights the airport can manage. It is calculated by the designed hourly capacity of the airport runway times the number of operating hours (we assume all the airports in the selected cities operate 18 h a day, from 6:00 am to 24:00 pm). The data is obtained from Airport Master Plans (2022).
- 14) HSR train capacity of the station: means the maximum number of high-speed trains the station can manage. The figure is used by the maximum daily train numbers in 2019 for each city. The data is obtained from 12,306 China Railway (2019).

4.2.2. Parameters for hierarchy 2

The second set of parameters, elucidated below, are instrumental in characterising the temporal dimensions of the system. Each parameter is underpinned by specific data sources and calculations that are pivotal to

our understanding of the intricate temporal dynamics within the transport network.

- 1) Time windows: time windows are set as every 10 min (e.g. 8:00 am - 8:10 am) for both airports and HSR stations.
- 2) Transfer time: the appropriate transfer time from the airport to the HSR station, and the transfer time from the HSR station to the airport is calculated as follows.

Air to HSR: Airport terminal domestic arrival time + Ground transport time + Station departure processing + Station dwell time
 HSR to Air: Station arrival time + Ground transport time + Airport terminal domestic departure processing time + Airport terminal dwell time

Among which, the directional ground time is using the shortest ground time searched with Gaode map (2023); airport domestic arrival time, departure processing time and dwell time is acquired from the interview with terminal manager of Beijing Capital Airport; HSR station departing processing time, dwell time and arrival time is observed in Beijing Chaoyang Station.

Furthermore, to account for potential delays and ground congestion, a grace period is incorporated in both directions as follows.

Flight Delays: In the case of air-to-HSR connections, we will introduce a maximum 30-min grace period to account for potential flight delays in arrival.

Ground Congestion: For both air-to-HSR and HSR-to-air connections, we will include the same 30-min grace period to accommodate possible congestion in ground transportation.

HSR Punctuality: Given that China's HSR system has a punctuality rate of over 98 % (for departures) and over 95 % (for arrivals) as noted by [Lawrence et al. \(2019\)](#), we will not apply a grace period for air-to-HSR connections, since the HSR processing time for departure remains unchanged. However, for HSR-to-air transfers, we will still add a 30-min grace period to the HSR arrival time to account for any possible delays and to ensure travellers have sufficient time for ground transport to the airport.

- 3) Flight timetable: among the 40 cities, the actual flight schedule is obtained from the OAG schedule database ([OAG, 2022](#)), and the date is selected as 12 December 2019 data, as many air routes were closed during COVID.
- 4) HSR timetable: among the 40 cities, the actual daily schedule is obtained from 12,306 China Railway (2019), as many HSR routes were closed during COVID.
- 5) Time window capacity of the airport: this means the maximum number of flights the airport can manage in each time window. It is calculated by the designed hourly capacity of the airport runway divided by 6 (6 time windows per hour). The data is obtained from Airport Master Plans (2022).
- 6) Time window capacity of the station: means the maximum number of high-speed trains the station can manage in each time window. The number is calculated by the maximum daily train numbers in 2019 for each city divided by the number of operating hours per day (assuming 18 h, from 6:00 am to 24:00 pm) and then divided by 6. The data is obtained from 12,306 China Railway (2019).

4.3. Results

4.3.1. Results for hierarchy 1

4.3.1.1. *Social welfare perspective.* The above problem was programmed in Python to model the air-HSR network between 40 cities and solved by Gurobi Optimiser version 9.5.0. Gurobi employed a combination of techniques to solve the model, including presolve, cutting planes, and the branch-and-bound algorithm. After initial optimisation of the allocation, it takes 0.41 s to converge to near-optimal solution with a minimal optimality gap of 0.94 %.

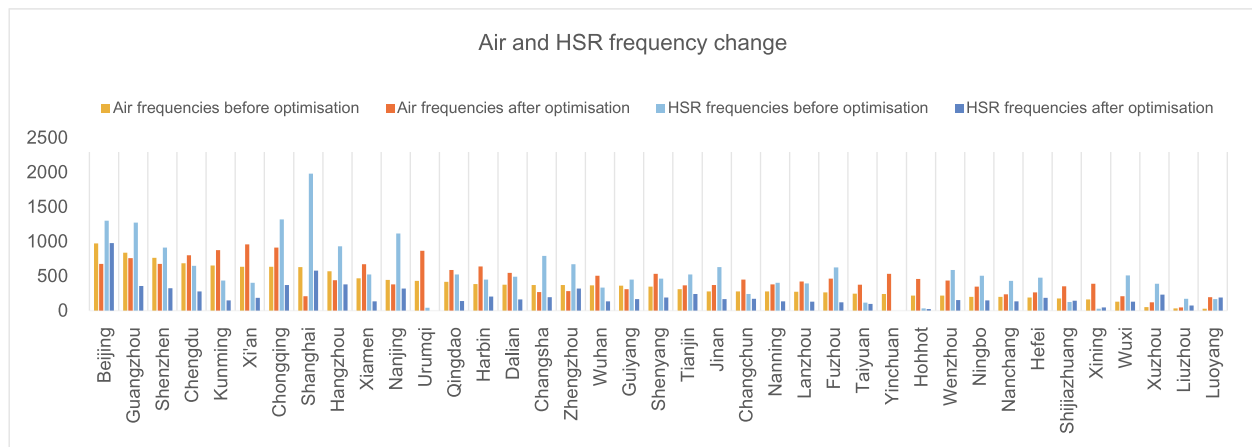


Fig. 4. Air and HSR frequency change in each city per day.

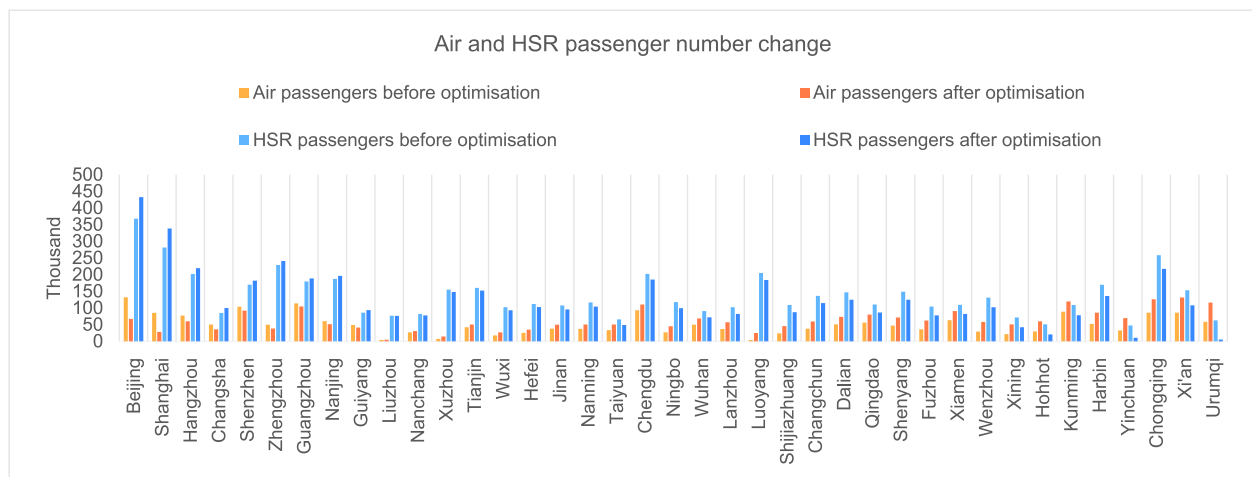


Fig. 5. Air and HSR passenger number change in each city per day.

The initial model comprised 11,092 constraints and 5928 decision variables, resulting in a total of 18,500 non-zero coefficients. To enhance computational efficiency, a presolve phase was executed, wherein Gurobi identified and eliminated 9874 redundant constraints and 4273 variables. This reduction transformed the model into a more tractable form, leaving 1101 constraints and 1655 decision variables, with the presolve phase concluding in just 0.10 s. Throughout the optimisation procedure, Gurobi applied a series of cutting planes, including Gomory cuts and mixed-integer rounding (MIR) cuts, which served to tighten the linear programming relaxation of the model. The resolution of the root relaxation yielded an objective of approximately 11.53 billion after 589 simplex iterations.

In the optimisation of the original demands, that is, before the demands have been changed by the results of the second hierarchy of optimisation, as shown in Fig. 4 and Fig. 5, the allocation of passengers between the 40 cities and the frequency allocation have changed significantly compared to the status quo when emissions, passenger time, fare costs and operating costs are taken into account. Overall, the number of passengers allocated to HSR in the network decreases from 2.70 million to 2.48 million per day, while the number of passengers allocated to air transport increases from 0.99 million to 1.20 million per day. Of the 40 cities, only 9 cities, including Beijing, Shanghai and Hangzhou, saw a decrease in the number of flight passengers, while the rest saw an increase in the flight passengers, with Urumqi and Xi'an seeing the largest increases; at the same time, the number of people travelling by HSR decreased in these 9 cities, while the rest saw an

increase in the number of people travelling by HSR. This suggests that there is significant upside demand for air travel on many routes other than the busiest airports, and that it still has a strong competitive advantage over HSR.

Similar as the distribution of the number of passengers, the overall HSR daily frequency decreased from 10,692 to 4409 after optimisation, while the daily frequency of flights increased from 7390 to 8922. Of the 40 cities, only 9 cities, including Beijing, Shanghai and Hangzhou, saw a decrease in flight frequency, while all other cities saw an increase in flight frequency, with the largest increases in Urumqi and Xi'an, with 432 and 325 additional flights daily. In contrast to flights, 36 of all cities experienced a decrease in the frequency of HSR, with 30 cities experiencing a reduction of more than one hundred frequencies per day, and only three cities (Shijiazhuang, Xining and Luoyang) experiencing a slight increase in daily frequencies. This indicates, on the one hand, that there is currently a large amount of redundancy in the number of seats operated by HSR in China, with supply far outstripping demand; on the other hand, it indicates that these 40 cities, as the larger cities in China, have a higher flight load factor than the national average in 2019 (83.2 %), and therefore need more flights to accommodate the strong passenger demand. At the same time, the emission factor does not have a decisive impact on the optimisation results, as the unit carbon price is relatively low in China.

Overall, the number of routes where both air and HSR exist while meeting the demand for travel between the 40 city pairs has been significantly reduced, with the number of directional routes where air

and HSR overlap reduced by 83 % from 623 to 107. The number of routes between the 40 city pairs where only one mode of transport is available, either air or HSR, has increased from 818 to 1418. Currently, 484 routes are not served by air or HSR, but only by regular trains or buses. After optimisation this number has been reduced to 64, meaning that network connectivity has increased. These city pairs are because the current travel demand is low and can be met by transit from other cities or other ground transport modes. Three cities (Yinchuan, Urumqi and Jieyang) are found not to require HSR operation after optimisation, presumably due to their remote location and weak demand. They can currently be met by air or by transit from neighbouring major cities. The result of the optimisation has significantly reduced redundant air and HSR operations.

The findings reflect a more efficient use of air travel for routes where it has comparative advantages (e.g., long-haul flights) and a shift of shorter, less efficient flights to HSR. This aligns with research suggesting that for certain distances, particularly under 700 or 800 km, HSR can serve as a more efficient and environmentally friendly alternative (ICCT, 2022). After the optimisation, as shown in Fig. 6, daily emissions decreased in all 40 cities, with the decrease in inbound and outbound emissions per city ranging from 0.19 kt per day to 12.9 kt per day, and the total daily emissions in the network decreased from 236 kt to 184 kt. These results indicate that both air and HSR transportation modes play significant roles in determining emissions. Calculated with China carbon price, the total emission cost drops from 13.95 million yuan/day to 11.30 million yuan/day. As a result of the decrease in the number of passengers allocated to HSR and the increase in the number of air passengers, the overall fare cost for all passengers in 40 cities decreases from 14.41 billion yuan/day to 9.98 billion yuan/day. Average travel time per passenger (considering processing and dwell time) decreased from 4.44 h/day to 4.29 h/day, and total time value decreased from 1.17 billion yuan/day to 1.12 billion yuan/day. The number of daily flights has increased and aircraft are mostly scheduled on long-haul domestic routes, but the frequency of HSR operation has been greatly reduced, so the overall operating cost of aircraft and HSR has decreased from 1.38 billion yuan/day to 1.23 billion yuan/day. From the perspective of social welfare, taking into account the above four factors, the optimised overall cost of supply and demand between air and HSR across the 40-city network is reduced from 16.97 billion yuan to 12.34 billion yuan per day.

4.3.1.2. Environmental perspective. The optimal allocation results presented above represent the best distribution when social welfare—defined as the minimisation of four objective costs (fares, passenger

time, emissions, and operations)—is prioritised. The allocation outcomes differ, however, when each objective is considered independently, indicating that the weight assigned to emissions in the multi-objective optimisation has a minimal impact on the allocation. This finding suggests that while environmental costs are considered, they play a relatively minor role in shaping the overall network allocation when combined with other objectives.

When environmental emissions alone are set as the objective function, the allocation shifts more significantly to reflect intensive and efficient operations aimed at reducing emissions. In this scenario, both air and HSR frequencies decrease compared to the pre-optimisation. This adjustment demonstrates a prioritisation of emission reduction over service frequency, resulting in a more efficient use of resources. To meet inter-city travel demand within this framework, air passenger numbers decline, while HSR passenger numbers increase, indicating that HSR's lower emissions per trip make it the more environmentally favorable mode for short- and medium-distance travel.

In terms of specific cities, the emission-focused optimisation results in notable changes in service frequencies, compared to pre-optimisation. The frequency of HSR services decreases in 33 cities, including Shanghai, Guangzhou, and Chongqing, while air travel frequencies decline in 17 cities, notably Beijing, Shanghai, and Guangzhou. When comparing the results of emissions-only optimisation to those of the full-objective optimisation, we observe additional decreases in air frequencies in cities such as Nanjing, Wuxi, and Nanchang—bringing the total number of cities with reduced flight frequencies to 26. In contrast, with the exception of Hohhot, where HSR frequency remains unchanged, all other cities experience an increase in HSR frequency under the emissions-only objective. This outcome underscores HSR's lower per-trip emissions compared to aviation, making it a more favorable option under a carbon-minimising allocation.

As illustrated in Figs. 7–9, this emissions-focused allocation reduces network-wide daily emissions by an additional 20,000 t compared to the emissions level achieved under the full-objective optimisation. The shift toward HSR emphasises its role as a more sustainable option in the context of intermodal competition, as its environmental advantage becomes clearer when emissions are prioritised.

4.3.1.3. Passenger perspective. When the objective function is adjusted to focus solely on passenger costs, including both fares and time costs, the optimal allocation results bear a closer resemblance to those obtained when considering social welfare (fares, passenger time, emissions, and operations). This similarity suggests that passenger costs constitute a significant proportion of the total costs in the full-objective optimisation, highlighting their centrality to intermodal allocation decisions.

Compared to the pre-optimisation, the passenger-cost-focused allocation leads to an increase in flight frequency and air passengers, alongside a decrease in HSR frequency and passengers. These results reflect the inherent competitive advantage of air travel on medium and long-distance routes in terms of both fare costs and travel time. On these routes, flights can offer lower fares and shorter travel times, making them more attractive to passengers. Notably, routes such as Beijing–Kunming, Guangzhou–Chengdu, Chongqing–Wenzhou, and Chongqing–Fuzhou experience the highest increases in flight frequency. These are long-distance domestic routes where air fares are lower, and the extended travel time of HSR imposes higher time costs on passengers, reducing the competitiveness of HSR.

In contrast, the optimisation of HSR frequency is primarily driven by demand on shorter routes. The largest decrease in daily HSR frequency occurs on high-frequency short-distance routes, including Beijing–Tianjin, Beijing–Jinan, Shanghai–Nanjing, and Shenzhen–Guangzhou. These routes currently have high daily HSR frequencies, and the optimisation reallocates resources to balance demand and capacity more efficiently. Conversely, the highest increase in HSR frequency is



Fig. 6. Emission savings in each city per day by province.

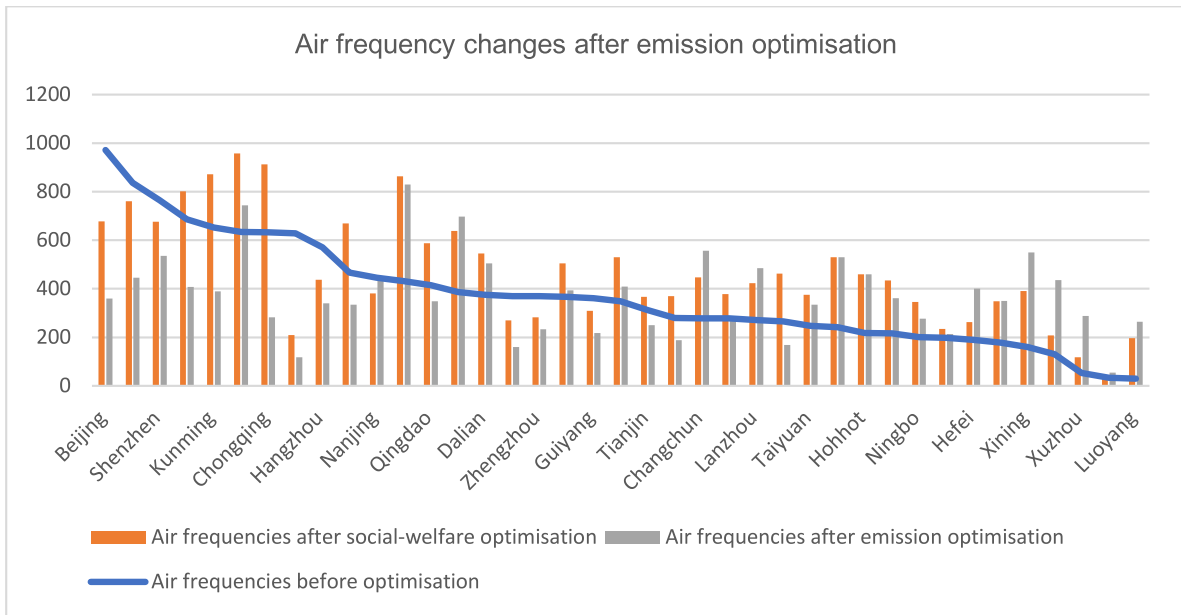


Fig. 7. Air frequency changes after emission optimisation.

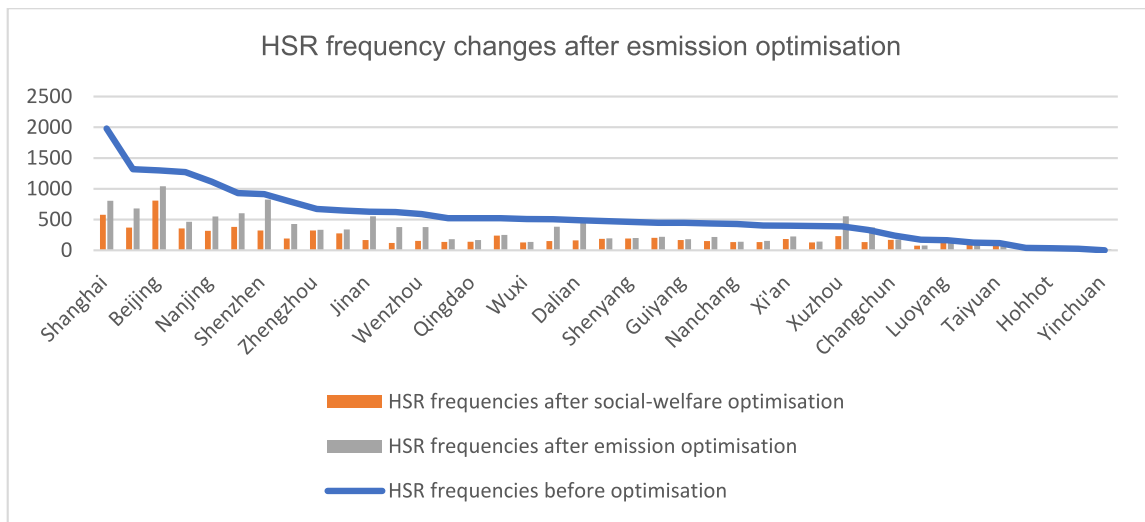


Fig. 8. HSR frequency changes after emission optimisation.

observed on lower-frequency, short-distance routes such as Zhengzhou-Luoyang, Harbin-Changchun, and Xuzhou-Nanjing. By increasing HSR frequency on these lower-demand routes, the model aims to enhance service availability where it is currently limited, potentially making HSR more attractive to travellers on these corridors.

As illustrated in Figs. 10–11, this passenger-cost-driven allocation scenario yields network-wide benefits in terms of both fare and travel time reductions. The average one-way fare for both flight and HSR passengers across the network decreases from 538.8 yuan per trip before optimisation to 530 yuan per trip. This reduction reflects a more cost-effective allocation that aligns with passengers' preference for lower fares, particularly on competitive routes. The average one-way travel time drops from 4.44 h per trip to 4.24 h per trip, indicating that the optimised allocation not only reduces monetary costs but also improves time efficiency, through increased flight frequencies on long-distance domestic routes.

4.3.2. Results for hierarchy 2

Hierarchy 2 is focusing on the connection opportunities and timetable coordination of air-HSR intermodal nodes obtained from hierarchy 1, by setting the service frequency adjustments to the appropriate time windows. The number of departure/arrival flights and trains assigned from step 1 provides the constraints and optimising direction for this step. The network and the corresponding timetable we work on are still within the 40 cities. Considering the variability and complexity of schedules in different cities, Beijing is selected as an example for detailed analysis of hierarchy 2. As mentioned earlier, we utilise directional segmentation measurements to estimate transfer times between airports and HSR stations in hub cities.

As shown in Fig. 12, in the first hierarchy, we have obtained the optimised number of changes in the daily frequency of flights and HSR from Beijing to each city and from each city into Beijing, e.g., Shenzhen-Beijing are reduced by 11 flights per day and the HSR is increased by 19 frequencies per day, comparing with current 36 inbound flights and 6 inbound HSR trains; while Beijing-Shenzhen flights are reduced by 10

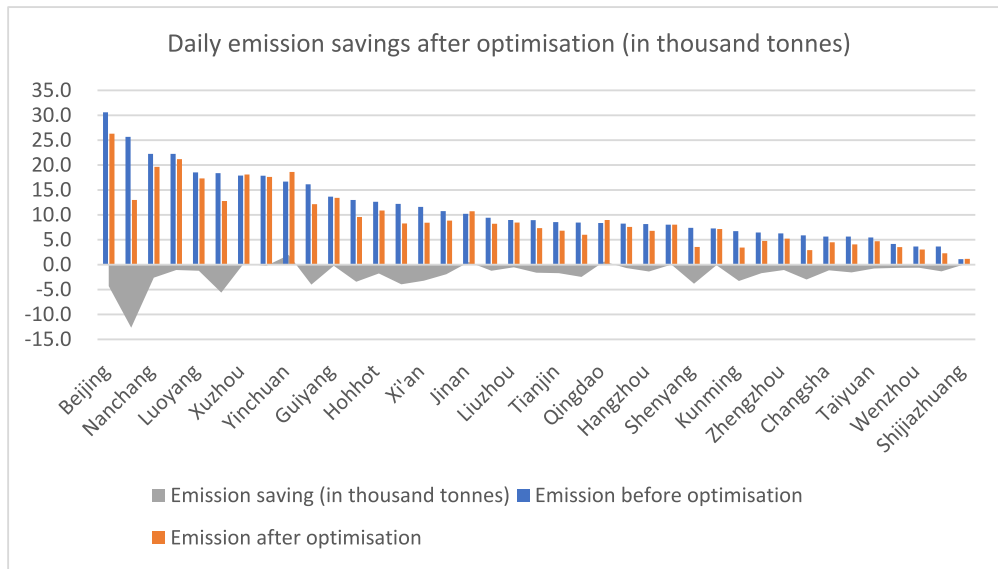


Fig. 9. Daily emission savings after optimisation

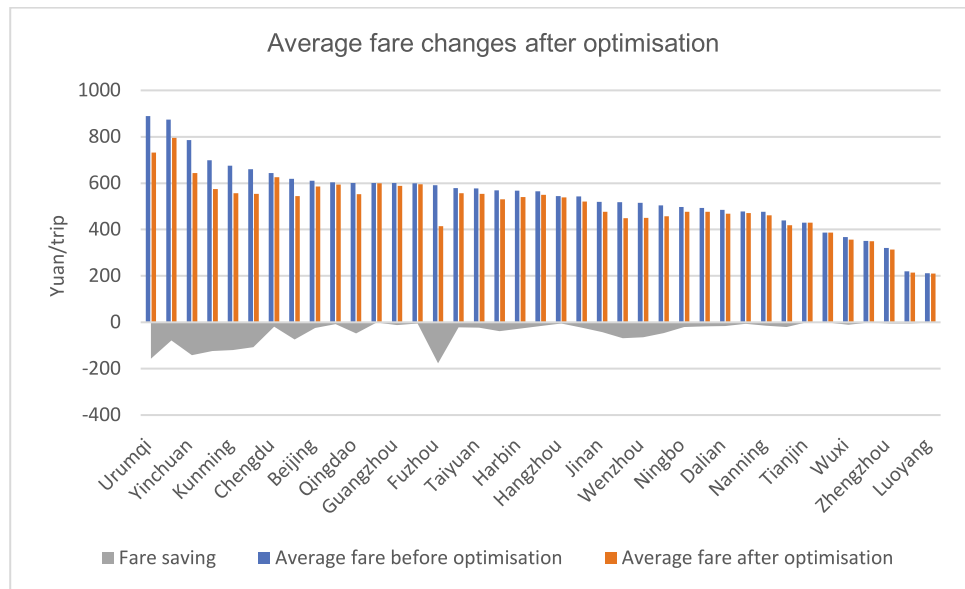


Fig. 10. Average fare changes after optimisation.

flights per day and the HSR is increased by 20 frequencies per day, comparing with 35 outbound flights and 5 outbound HSR trains currently. In the second hierarchy, our goal is to find the slots in the existing schedule where these changes in frequency can be increased or decreased to maximise the opportunities for air and HSR connections between the time windows allowed for each transfer time range, between 6:00 and 24:00 in the Beijing hub during the day (assuming that travellers stay overnight after 0:00).

The model is solved by LINGO version 18.0, the problem class is identified as “Pseudo-Integer Quadratic Programming”, branch and bound algorithm is employed. Despite the optimised reduction in the frequency of domestic flights and HSR in Beijing, connection opportunities have been maximised to maintain connectivity and convenience. After more than 1.04 million iterations and a time of 10 min and 24 s, the most combinations of air-HSR intermodal transport opportunities in Beijing in a day are obtained. There are 5721 combinations of air-HSR intermodal transport opportunities in Beijing in a day, among which

2621 service combinations of arriving HSR connecting to departing flights and 3100 combinations of arriving flights connecting to departing HSR. The decrease in frequency resulted in no increase in the number of overall transfer opportunities and therefore did not stimulate new passenger demand and did not enter the next cycle of frequency optimisation.

At the same time, we identified the optimal time windows for adjusting the frequencies of each mode to and from Beijing to maximise intermodal connections. These adjustments are based on the current timetables, meaning that only the specific services requiring addition or removal are scheduled at appropriate times, ensuring minimal overall changes to the existing schedule. For instance, comparing the current flight departure schedule shown in Fig. 13 (where the number represents the number of flight departures within each time window to a given city), we find that one outbound flight to Hohhot (HET airport) is removed between 6:00–6:10, as shown in the adjusted flight schedule in Fig. 14 (where “1” indicates one additional flight required and “-1”

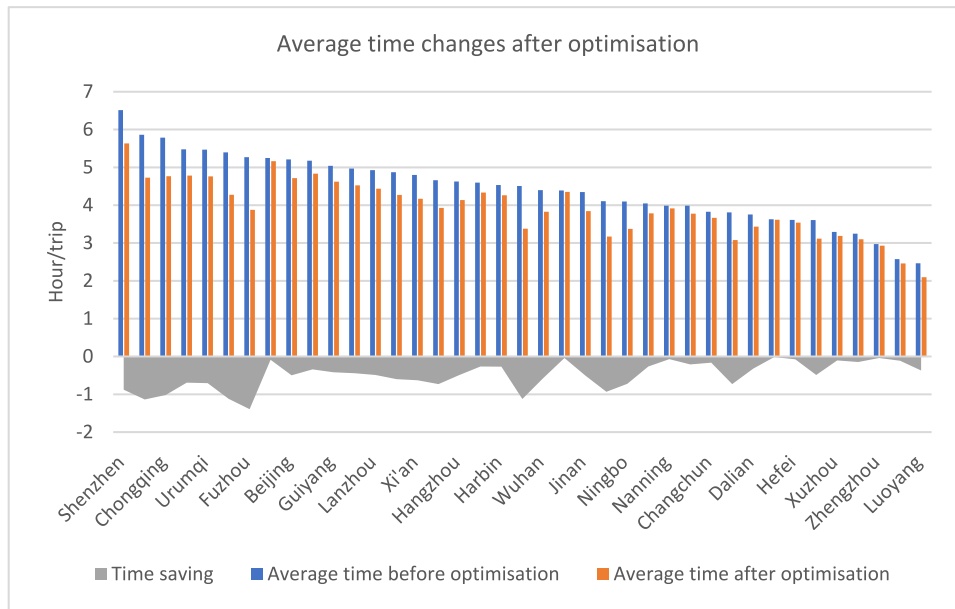


Fig. 11. Average time changes after optimisation.

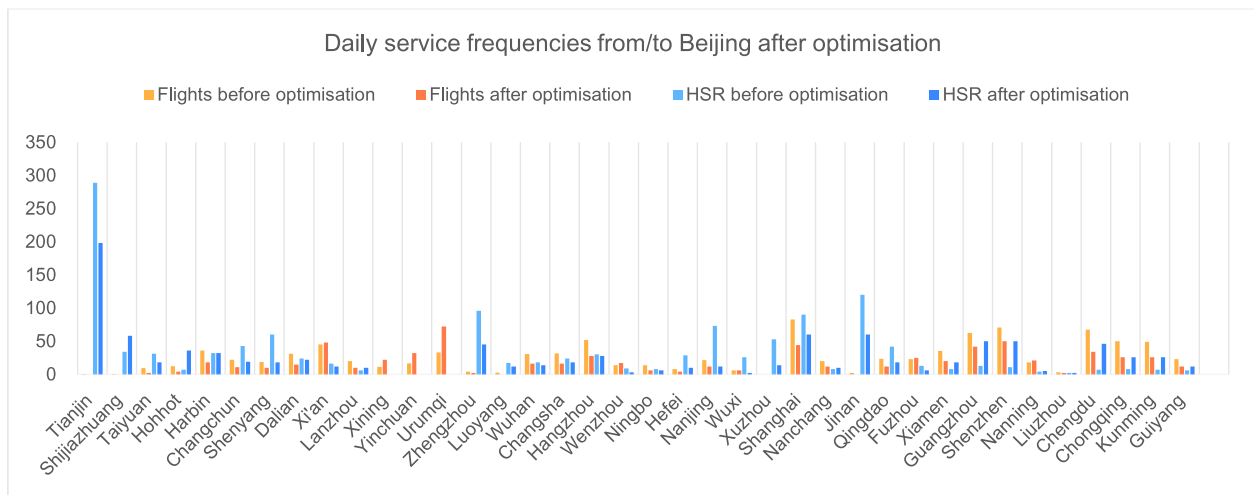


Fig. 12. Air and HSR frequency change from/to Beijing per day from hierarchy 1.

indicates one flight reduction in a given 10-min window relative to Fig. 13).

For flight arrivals, relative to the current schedule in Fig. 15, Fig. 16 shows that one arrival flight from Wenzhou (WNZ airport) is added between 6:00–6:10, while one flight from Chengdu (CTU airport) is removed between 6:30–6:40. Similarly, comparing the current schedule for HSR departures in Fig. 17, Fig. 18 shows that between 6:00–6:10 there are three outbound train reductions, affecting services to Tianjin, Shijiazhuang, and Hohhot.

Regarding HSR arrivals, Fig. 20 (compared with the current schedule in Fig. 19) shows two added inbound trains between 6:00–6:10 from Tianjin and Taiyuan. A summary of these frequency adjustments for flights and trains to and from Beijing throughout the day is provided in Figs. 21 and 22, respectively.

After the schedule adjustment, if we only focus on one corresponding city, we can also know how the flights/trains departing from and arriving at Beijing in that city are adjusted during the day. Take the Beijing-Shanghai city pair as an example, the current outbound (Beijing-Shanghai) and inbound (Shanghai-Beijing) flights are scheduled in the

SHA column of Fig. 13 and Fig. 15, as shown in Figs. 14 and 16, the earliest departure flight adjustment occurs at 9:00–9:10, and the earliest arrival flight adjustment occurs at 9:20–9:30. Similarly, we can see from Figs. 18 and 20 that, for both departure and arrival, there is one HSR service removed at 6:10–6:20, and another service added at 6:20–6:30. The service adjustment allocation for air and HSR between Beijing and Shanghai along the day is summarised in Fig. 23.

5. Sensitivity analysis

In the above baseline analysis of this study, specific assumptions were made for key parameters such as demand, carbon price, and ticket prices to establish a clear and consistent foundation for the model. These assumptions allow for a controlled environment to optimise the service and passenger allocation, meanwhile assess the impact of existing conditions. However, recognising that real-world conditions vary, we will conduct a sensitivity analysis on these critical parameters to explore how changes affect the allocation between air and HSR under different scenarios.

Air	TSN	SJW	TYN	HET	HRB	CGQ	SHE	DLC	XIY	LHW	XNN	INC	URC	CGO	LYA	WUH	CSX	HGH	WNZ	NGB	HFE	NKG	WUX	XUZ	SHA	KHN	TNA	TAO	FOC	XMN	CAN	SZX	NNG	LZH	CTU	CKG	KMG	KWE		
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Fig. 13. Current schedule for flight departures to each city from Beijing.

First, we will vary demand to account for peak and off-peak travel seasons, as demand typically fluctuates significantly based on the time of year. Second, the carbon price used in the baseline was based on China’s carbon market price. To test the role of carbon prices in optimising allocations, we will examine how increasing the carbon price to levels seen in the European Union Emissions Trading System (EU ETS) impacts the allocation and the cost-effectiveness of air and HSR services. Lastly, while we used historical HSR ticket prices in the baseline analysis, we acknowledge that certain routes have seen recent price increases in China (New York Times, 2024). Therefore, we will incorporate HSR price fluctuations to assess how future price adjustments could shift passenger preferences and mode selection.

5.1. Demand fluctuations

The average city-pair demand in the baseline scenario was estimated using population size, migration index, daily outgoing trip proportion, and resident income level. However, actual demand can vary significantly from day to day. For example, demand for cross-city travel may surge several times above normal levels during holidays, while unusual events, such as epidemics, may cause a sharp decline in intercity trips. To account for this variability, we applied demand fluctuations of ± 10

% and ± 20 % across all cities based on the average baseline demand.

From the baseline analysis, we observed that flight supply in these 40 city networks is generally aligned with demand, while high-speed rail supply substantially exceeds demand. Thus, when demand increases, we assume the maximum capacity for flights can be adjusted proportionally, while the HSR supply limit remains unchanged. Conversely, when demand decreases, no adjustments are made to the supply ceilings for either flights or HSR services.

The results, as shown in Fig. 24, show a clear linear relationship between demand changes and total social costs (time costs, fares, operations, and emissions), with higher demand leading to higher total costs. The total cost rises to 14.0 billion yuan with a 20 % increase in demand and drops to 9.27 billion with a 20 % decrease.

For the proportion of changes in allocation and costs in response to demand, as shown in Table 3, flight frequencies increase by 19.6 % with a 20 % rise in demand and decrease by 18.5 % when demand falls by 20 %. This indicates that flight frequency adjusts almost proportionally with demand, though slightly more conservatively. Flight passenger numbers grow by 20.4 % with a 20 % rise in demand, showing a highly linear relationship between demand growth and air travel passenger numbers. With a 10 % drop, air passenger numbers decrease by 9.9 %, again showing a direct proportional impact. On a route-by-route basis,

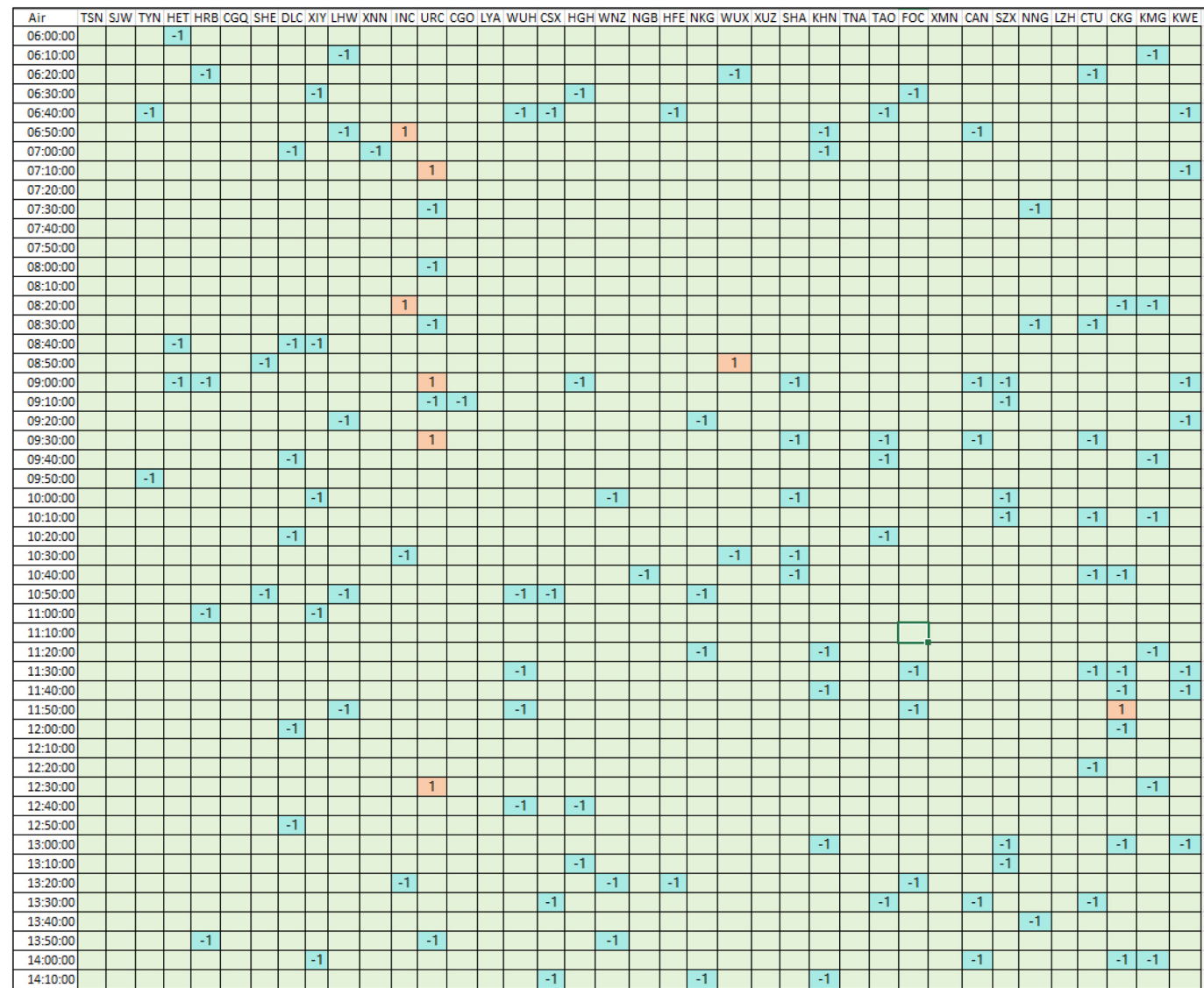


Fig. 14. Schedule change for flight departures to each city from Beijing.

the frequency of flights and the allocation of passengers also increases or decreases proportionally to the increase or decrease in passenger demand. Taking flights originating in Xi'an as an example, as shown in Fig. 25, the number of flights from Xi'an to each city varies proportionally with the change in total demand.

HSR frequencies show a similar behaviour, increasing by 18.2 % when demand increases by 20 % and falling by 18.5 % with a 20 % decrease in demand. The change in HSR frequency is nearly proportional to demand, though slightly less responsive compared to flights. HSR passengers increase by 19.8 % with a 20 % demand rise and drop by 20.2 % when demand falls by 20 %. This suggests that HSR passenger allocation is very closely tied to demand changes, with a near one-to-one correspondence. In terms of individual routes, the frequency of HSR and passenger allocation also increase or decrease in direct proportion to the increase or decrease in passenger demand. Taking the HSR arrivals in Xi'an as an example, as shown in Fig. 26, the number of HSRs from most cities to Xi'an is proportional to the change in total demand, while a few cities with fewer daily frequencies, such as Wuxi and Liuzhou, have HSR frequencies that do not change with demand.

An interesting finding is that the rate of change in passenger numbers consistently exceeds the rate of change in service frequencies. When demand increases, the rise in the number of passengers is proportionally

larger than the increase in service frequencies. For example, with a 20 % increase in demand, the number of air passengers grows by 20.4 %, whereas air frequencies increase by only 19.6 %. Similarly, for HSR, the passenger growth is 19.8 %, while the frequency growth is lower at 18.2 %. This divergence suggests that as demand rises, the load factors for both air and HSR services increase, resulting in higher passenger occupancy per flight or train. This enhanced utilisation of available capacity makes the system more cost-efficient and may lead to improved profitability for operators.

Conversely, when demand declines, the reduction in passenger numbers also exceeds the reduction in service frequencies. For instance, with a 20 % decrease in demand, the number of air passengers drops by 19.7 %, while air frequencies decrease by only 18.5 %. Similarly, for HSR, passenger numbers decline by 20.2 %, whereas frequencies fall by 18.5 %. This imbalance indicates that a decrease in demand leads to underutilized services, with lower passenger occupancy per service. Such a situation reduces cost-efficiency, as the fixed operational costs are spread over fewer passengers, leading to potential losses unless further frequency adjustments are made.

Air	TSN	SJW	TYN	HET	HRB	CGQ	SHE	DLC	XIY	LHW	XNN	INC	URC	CGO	LYA	WUH	CSX	HGH	WNZ	NGB	HFE	NKG	WUX	XUZ	SHA	KHN	TNA	TAO	FOC	XMN	CAN	SZX	NNG	LZH	CTU	CKG	KMG	KWE	
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Fig. 15. Current schedule for flight arrivals from each city to Beijing.

5.2. Carbon price fluctuations

In the initial full-objective optimisation, where emissions were included as part of the objective function, it was observed that the current carbon price in China is relatively low compared to international level. As a result, the carbon emission cost represents only a small fraction of the total costs in the optimised allocation, effectively rendering it insignificant in the allocation process. To address this limitation and understand the potential effects of a higher carbon price, we assume a gradual increase in China’s carbon price to match the level of the EU ETS, where the average price in September 2024 was approximately 65.51 euros per tonne (Statista, 2024), equivalent to around 504 yuan per tonne.

To model this gradual increase, we conduct a sensitivity analysis using incremental stages, assuming the carbon price in China rises in four steps, each with an increase of approximately 185 %. The prices at each stage are set at 171, 282, 393, and 504 yuan per tonne. This staged approach allows for an analysis of how rising carbon prices might influence the allocation of travellers between air transport HSR and the overall cost structure of the transport network.

As shown in Table 4, the results indicate that increasing the carbon price has only a marginal impact on the allocation of passengers

between aviation and HSR as well as on the total cost of the system. Specifically, as the carbon price increases from 60 yuan to 504 yuan per tonne, the frequency of flights and the number of passengers allocated to aviation experience a slight decrease, while HSR passenger allocation rises modestly. Notably, the frequency of HSR services remains unchanged, suggesting that reducing the number of flights can be an effective cost-reduction strategy under higher carbon pricing without necessitating an increase in HSR capacity.

This shift in allocation leads to a modest reduction in total emissions across the network. Specifically, by adjusting flight frequencies and reallocating passengers to HSR, daily emissions can be reduced by approximately 153.29 t. This outcome highlights the potential for carbon pricing to incentivise more sustainable travel choices by favouring modes with lower emissions, particularly over shorter distances.

An analysis of specific routes reveals that the reduction in flight allocation and increase in HSR passenger numbers are most pronounced on shorter-distance routes, such as Hangzhou-Hefei, Guangzhou-Wuxi, and Guiyang-Kunming. This suggests that replacing flights with HSR on shorter routes can yield significant environmental benefits by lowering overall emissions. The findings imply that integrating HSR for shorter domestic routes could be a valuable strategy in minimising the carbon footprint of intercity travel within China as carbon pricing becomes

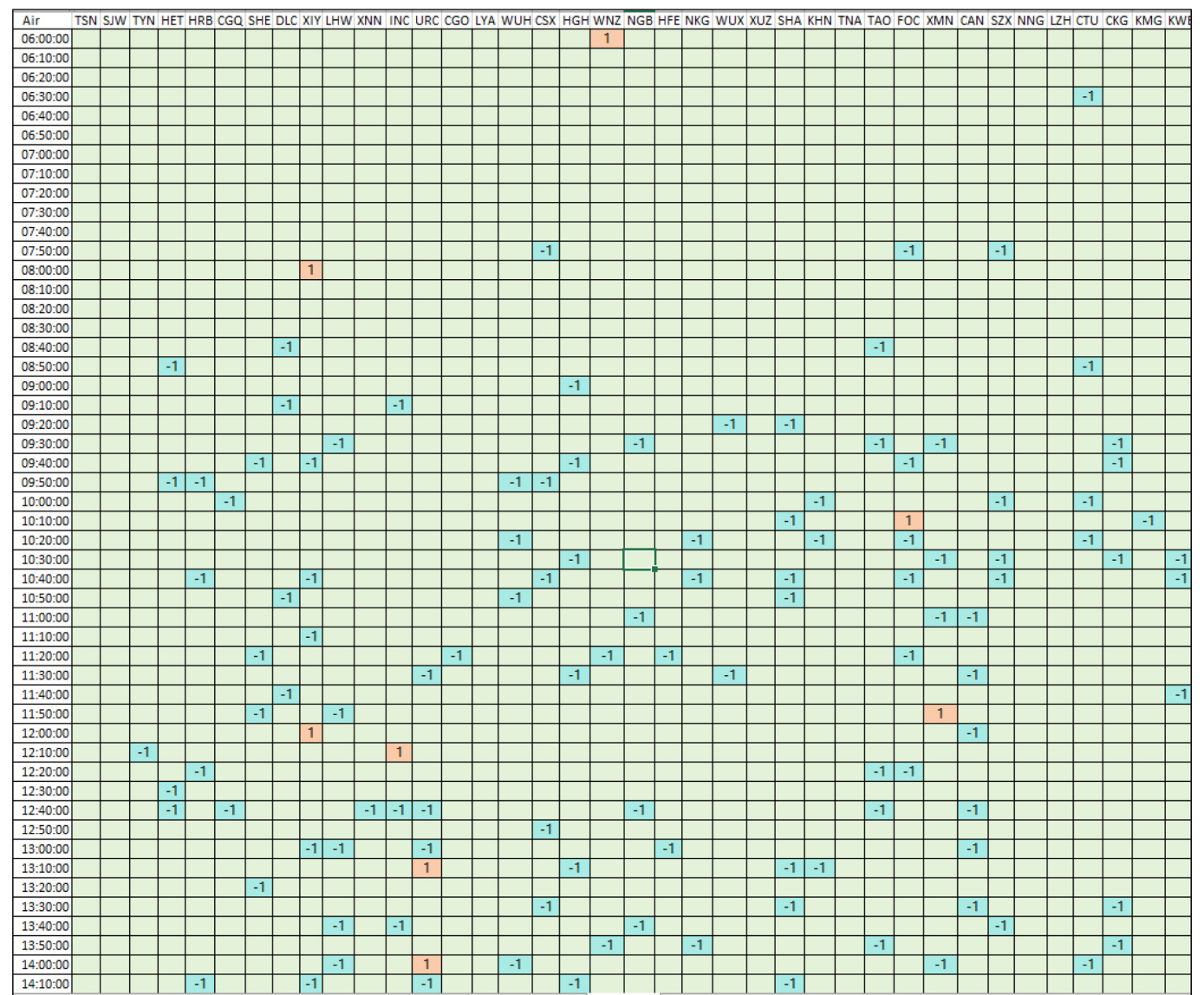


Fig. 16. Schedule change for flight arrivals from each city to Beijing.

more stringent.

5.3. HSR price fluctuations

Price changes are a crucial factor affecting demand allocation across transportation modes. The comparison of the full-objective optimisation and the passenger cost objective optimisation in previous sections reveals that passenger cost is the most significant component of the full-objective cost, with fare costs being the largest contributor to passenger expenses. Recent fare increases in China’s HSR system highlight the importance of this factor. According to *The New York Times* (2024), since June 2024, China’s HSR network has raised fares by approximately 20 % on selected segments across four major routes, including the Beijing-Guangzhou and Shanghai-Kunming lines. Furthermore, Zhang et al. (2019) report that intermodal competition significantly reduces air fares and frequencies. Specifically, on routes with HSR service, air fares are, on average, 0.397 RMB/km (34 %) lower, and air frequencies are reduced by 60.2 %. HSR competition also affects the price-distance relationship for air travel, with air fares reaching their lowest per-kilometre rates on routes around 1500 km in length.

Among the city pairs analysed in this study, 390 routes feature lower

air fares than HSR, while 145 routes have higher air fares. This variability suggests that HSR fares may either continue to rise due to cost and debt pressures or decrease to stay competitive with air travel. To explore the impact of HSR fare changes on the allocation between air and HSR, as well as on total network costs, we applied a sensitivity analysis with adjustments of ±10 % and ± 20 % to historical HSR fares across the study cities.

As shown in Fig. 27, when HSR fares increase, there is a small but noticeable shift in passenger allocation from HSR to air travel, prompting a slight increase in flight frequency to accommodate this shift and a corresponding decrease in HSR demand. Conversely, when HSR fares decrease, both air frequency and air passenger number experience a sharp decline. This reflects the fact that lower HSR fares enhance the attractiveness of rail travel, incentivising passengers to switch from air to HSR, thus reducing the demand for flights. The increased demand for HSR services can be efficiently met by increasing HSR frequencies, which accommodates the additional passengers and improves network utilisation.

While changes in HSR fares affect both transport modes, the impact is asymmetric depending on the direction of the price change, as detailed in Table 5. When HSR fares increase, the shift of passengers from HSR to

HSR	TSN	SJW	TYN	HET	HRB	CGQ	SHE	DLC	XIY	LHW	XNN	INC	URC	CGO	LYA	WUH	CSX	HGH	WNZ	NGB	HFE	NKG	WUX	XUZ	SHA	KHN	TNA	TAO	FOC	XMN	CAN	SZX	NNG	LZH	CTU	CKG	KMG	KWE		
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Fig. 17. Current schedule for HSR departures to each city from Beijing.

air is modest. For instance, a 20 % increase in HSR fares results in only a 1.9 % increase in air passengers and a 1.7 % rise in flights. This modest shift suggests that only a small fraction of HSR passengers are willing to switch to air travel in response to higher HSR fares. This resilience indicates that HSR passengers are attracted to rail travel for reasons beyond price, such as the convenience of city-centre connections, shorter boarding times, and potentially lower overall passenger costs when considering time costs in addition to fare costs.

Conversely, when HSR fares decrease, the shift from air to HSR is much more pronounced. A 20 % reduction in HSR fares leads to a 10.7 % decrease in air passengers and a 10.3 % decrease in flights. This significant reduction in air travel demand highlights the price sensitivity of air passengers in response to lower HSR fares. Many air passengers view HSR as a viable alternative, especially when it becomes more cost-competitive. The high degree of responsiveness suggests that air travellers, particularly those on short- to medium-haul routes, are highly sensitive to fare changes and are likely to switch modes if HSR becomes a more affordable option.

The analysis shows that price elasticity of demand for HSR is higher in the downward direction. When HSR prices decrease, a significantly larger proportion of passengers switch from air to HSR compared to the opposite scenario of an HSR price increase. This suggests that many air

passengers are price-sensitive and are willing to opt for HSR when it becomes more economical. Conversely, the choice of HSR passengers may be motivated by factors other than price (e.g., convenience), making them less likely to switch to air travel due to fare increases.

This differential impact is particularly evident on short-haul routes, where HSR competes most directly with air travel. On these routes, lower HSR fares prompt a large number of passengers to switch from air to rail, especially when HSR travel times are comparable to or shorter than air travel times when accounting for airport access and boarding procedures. For long-haul routes, however, the influence of HSR fare changes on air travel demand is limited, as air travel retains a time advantage over longer distances.

Moreover, high-demand routes connecting major urban centres, where both air and HSR services operate frequently, show heightened sensitivity to HSR fare adjustments. Reducing HSR fares on these routes leads to a substantial shift from air to HSR, which not only helps reduce congestion at airports but also improves network efficiency by optimising the use of rail infrastructure.

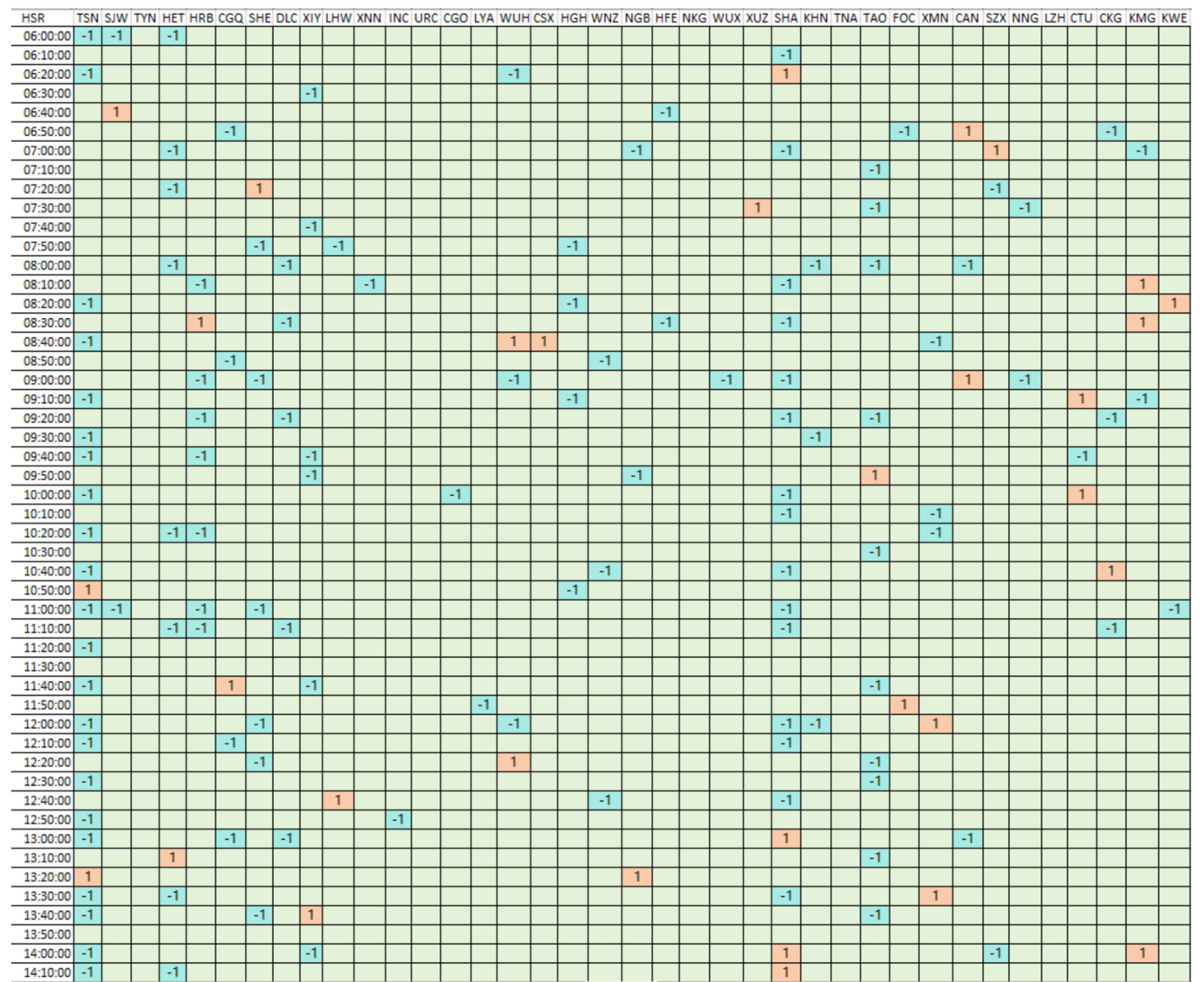


Fig. 18. Schedule change for HSR departures to each city from Beijing.

6. Policy implications

6.1. Enhancing strategic connectivity and collaborative optimisation

The model’s network-level approach to air-HSR integration highlights a strategic opportunity for national-level connectivity that goes beyond individual route, promoting a complementary relationship between air and HSR services. This aligns with recent policy priorities, as mentioned in the Strategic Cooperation Agreement on Promoting the High-Quality Development of Air-Rail Intermodal Transportation between the Civil Aviation Administration of China (CAAC) and the China State Railway Group, which prioritises intermodal connectivity over route-specific competition (CAAC, 2024). Policymakers can leverage this framework to support coordinated intermodal development, facilitating seamless connections between air and HSR modes across high-demand corridors and enabling a more efficient national network.

Policies encouraging collaboration among operators can drive efficient resource use and improve service quality, benefiting both the air and rail industries. Regulatory incentives, subsidies, and coordinated scheduling frameworks would support cross-operator alignment without compromising individual operators’ route-level strategies. For example, implementing tax incentives for routes with complementary air-HSR

connectivity could encourage airlines and HSR operators to prioritise strategic hub cities as intermodal nodes, optimising passenger flow and reducing redundancy. These incentives would allow for the mutual benefits of network effects in high-yield markets while using HSR as a sustainable alternative to short-haul air routes.

In practice, while the model presents an optimised allocation of resources and connectivity at the national level, it also empowers individual operators to make data-driven adjustments at the route level. For policymakers, this approach provides a scalable framework to guide infrastructure investments and service expansions that reflect both short-term operational needs and long-term strategic goals. Through this high-level coordination, national air-HSR integration can be enhanced to reduce network inefficiencies, improve access across urban and rural regions, and create a balanced, resilient, and sustainable intercity transport system.

6.2. Applying adaptive demand-supply management

The sensitivity analysis underscores the importance of adaptive demand-supply management in optimising the efficiency of the air-HSR network. The findings reveal that load factors are highly sensitive to demand fluctuations: as demand rises, services experience increased

HSR	TSN	SJW	TYN	HET	HRB	CGQ	SHE	DLC	XIY	LHW	XNN	INC	URC	CGO	LYA	WUH	CSX	HGH	WNZ	NGB	HFE	NKG	WUX	XUZ	SHA	KHN	TNA	TAO	FOC	XMN	CAN	SZX	NNG	LZH	CTU	CKG	KMG	KWE		
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Fig. 19. Current schedule for HSR arrivals from each city to Beijing.

load factors, improving profitability by maximising capacity utilisation. Conversely, when demand drops, services become less crowded, indicating a need to adjust frequencies to avoid underutilisation and associated inefficiencies. This fact highlights that maintaining an optimal balance between passenger demand and service frequency is essential to ensure efficient operations across both air and HSR modes.

For policymakers, this sensitivity to demand changes suggests that strategic service-level adjustments are key to avoiding excessive operational costs and maximising network performance. During peak periods, a smaller proportional increase in frequencies relative to demand growth can enhance load factors and revenue without adding unnecessary capacity, whereas in off-peak times, conservative reductions in service frequencies help manage costs without creating significant underutilisation. Policymakers should support regulatory frameworks and incentives that encourage flexible scheduling to adapt to seasonal demand fluctuations, ensuring that service supply aligns with real-time demand patterns.

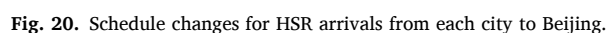
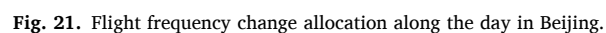
Moreover, the analysis shows that demand shifts have a disproportionately large impact on passenger allocation relative to service frequency adjustments. This insight implies that service redundancy should be minimised by reallocating resources to match demand distribution, avoiding the costs of over- or under-provision of services. A phased

approach to capacity expansion that aligns with demand growth—rather than frequent, large-scale infrastructure adjustments—ensures that infrastructure remains ready for future demand without incurring operational inefficiencies in the short term.

6.3. *Balancing passenger costs and emissions reduction*

The comparative analysis of cost-centred and emissions-centred objectives in the air-HSR network reveals key trade-offs for policymakers aiming to achieve both affordability and sustainability. When prioritising passenger costs (fares and travel times), the model suggests a configuration that favours increased air travel on medium- and long-haul domestic routes where air has a time advantage and offers competitive fares, leading to higher frequencies and passenger traffic for air travel. HSR, however, retains high frequencies on short-haul routes where convenience and demand support its competitiveness.

Conversely, when the objective shifts to minimising carbon emissions, the network allocation emphasises greater reliance on HSR for short- and medium-distance routes, where HSR offers lower per-trip emissions than air travel. In this environmentally focused configuration, air travel frequencies are significantly reduced on short-haul routes, where HSR can provide a viable alternative, and air



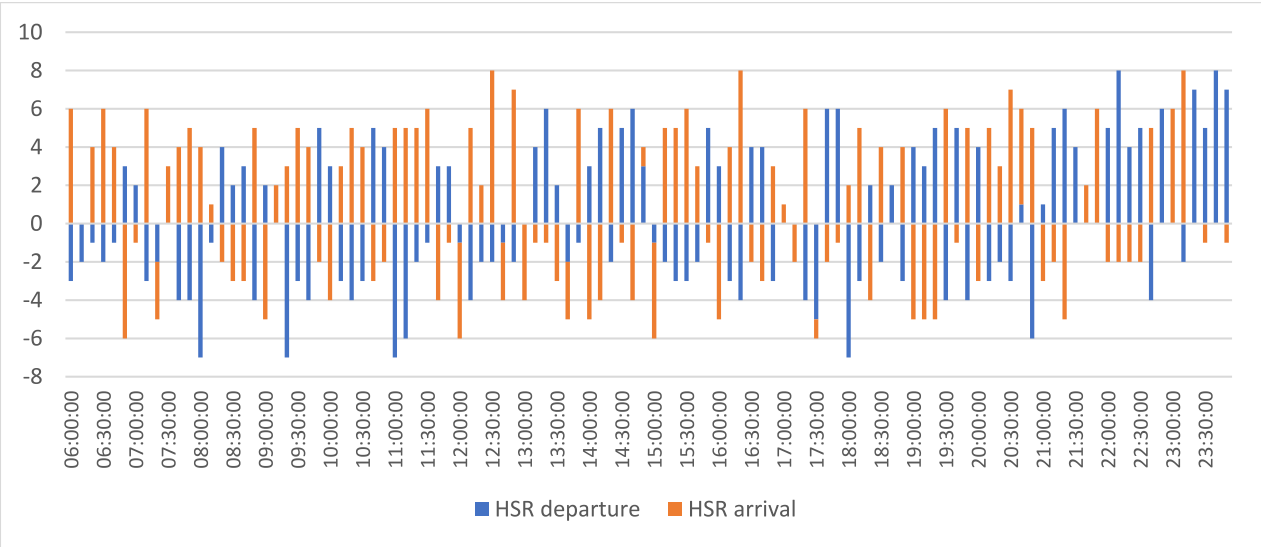


Fig. 22. HSR frequency change allocation along the day in Beijing.

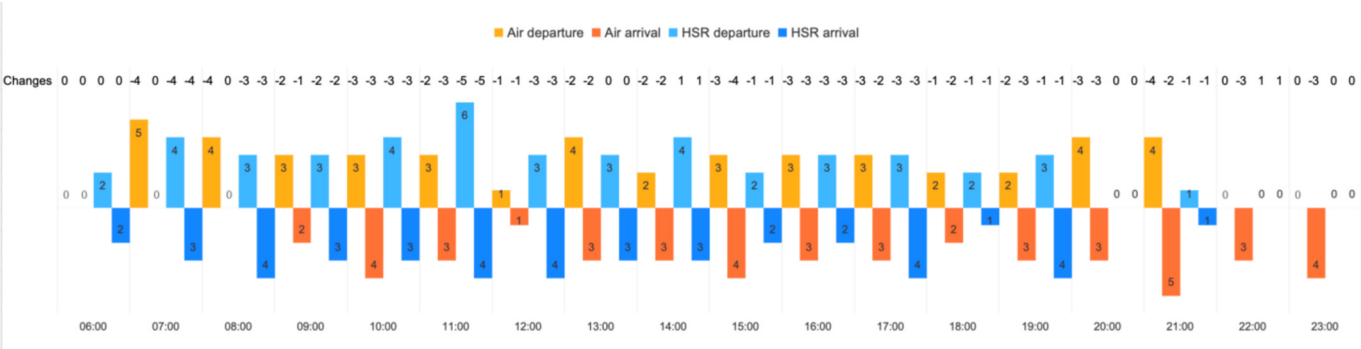


Fig. 23. Daily frequency allocation and changes between Beijing and Shanghai.

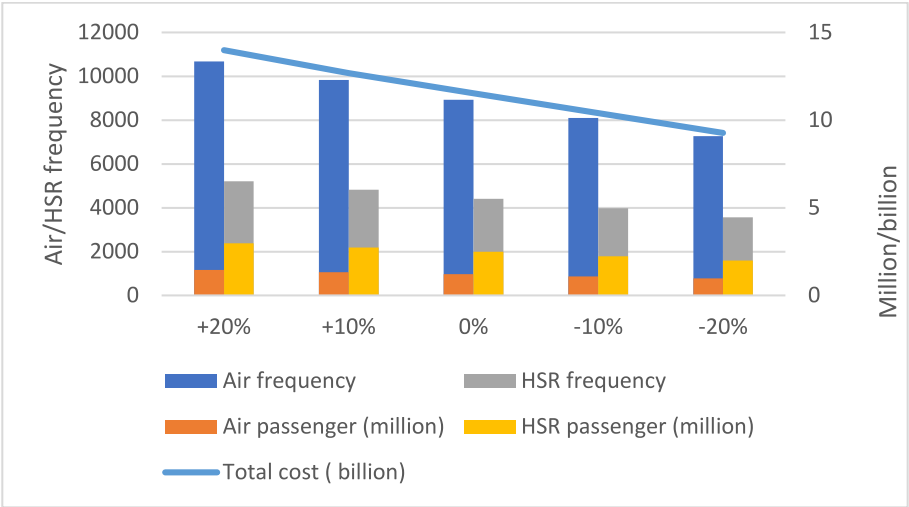


Fig. 24. Allocation results for demand sensitivity analysis.

frequencies are concentrated on longer domestic routes. This shift not only aligns with emission reduction targets but also reduces air congestion in densely travelled corridors, making HSR a replacement for environmentally sensitive routes. However, this approach may come at the expense of travel time efficiency and convenience, particularly on

longer routes where air travel is inherently faster. The carbon price sensitivity analysis demonstrates that incremental increases in carbon pricing would have a gradual but positive impact on emissions reduction, particularly on short-haul routes. Even under significant carbon price increases (e.g., to the level of the EU Emissions

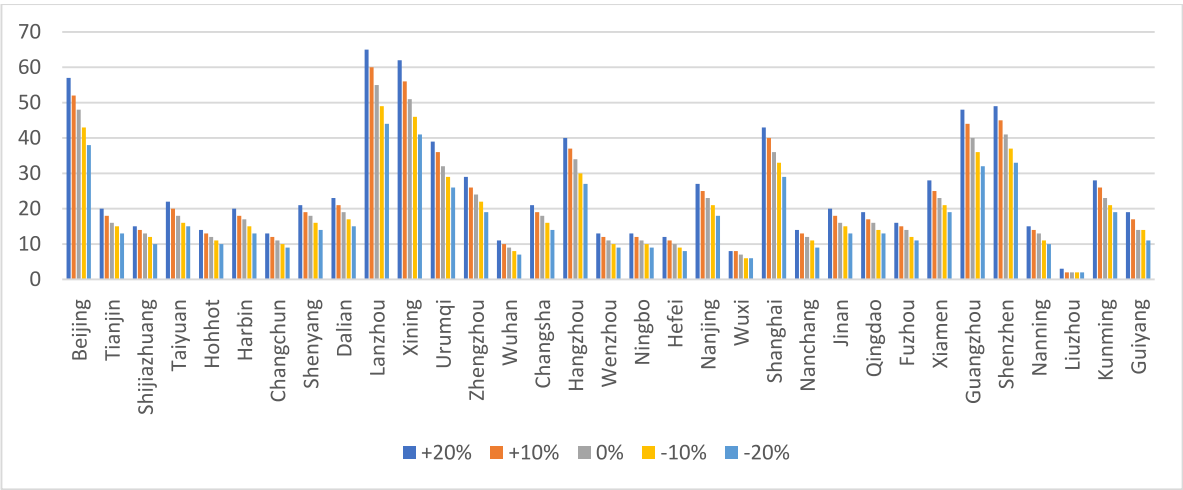


Fig. 25. Daily flight departures from Xi'an to each city under different demand scenarios.

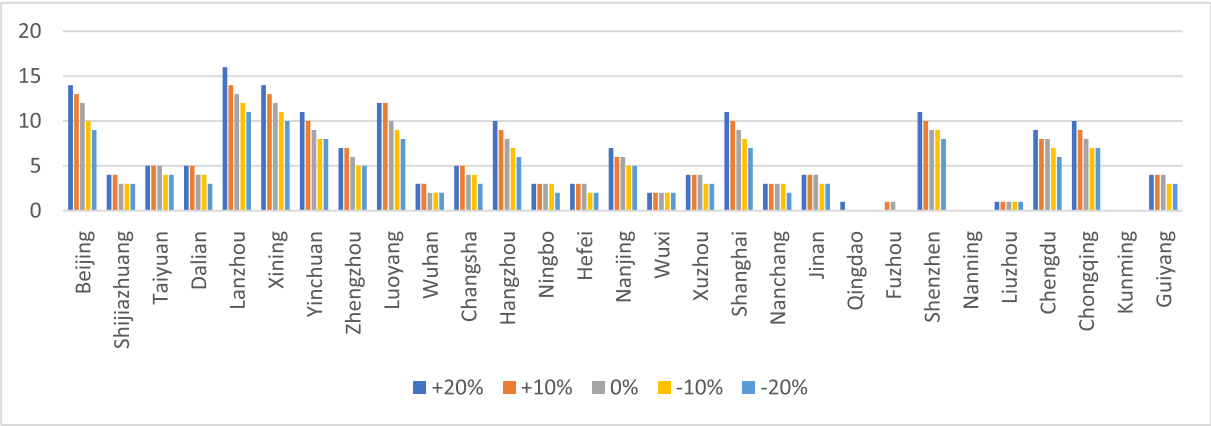


Fig. 26. Daily HSR arrivals from each city to Xi'an under different demand scenarios.

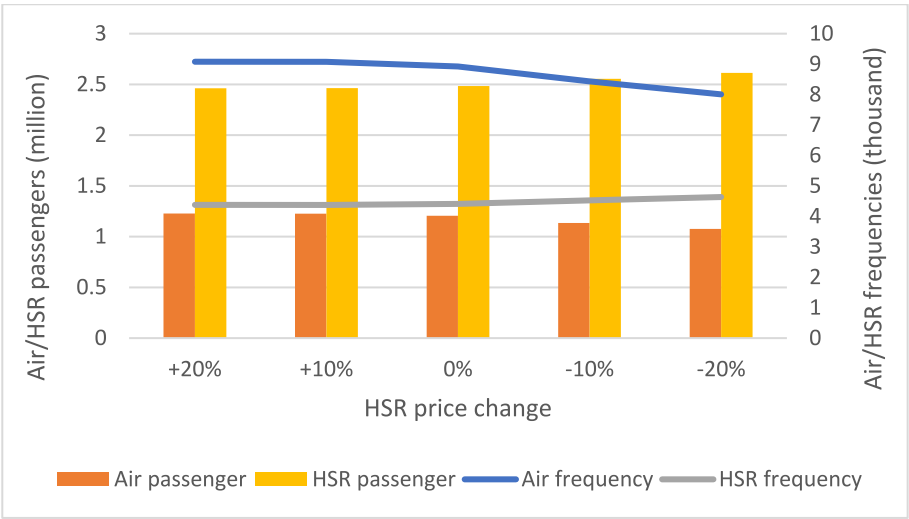


Fig. 27. Allocation results for HSR price sensitivity analysis.

Trading System), passenger redistribution between air and HSR is modest, with minor reductions in flight frequencies and a slight shift to HSR for short-haul routes. Notably, increasing HSR capacity is not required to accommodate this shift, suggesting that carbon pricing primarily affects air travel reductions rather than necessitating expanded HSR infrastructure.

Furthermore, route-level analyses reveal that carbon pricing has the greatest environmental impact on short-haul routes such as Hangzhou-

Table 3

Proportion of changes in allocation and costs in response to demand.

Demand change	Total cost change	Air frequency change	Air passenger change	HSR frequency change	HSR passenger change
+20 %	21.3 %	19.6 %	20.4 %	18.2 %	19.8 %
+10 %	9.9 %	10.1 %	10.0 %	9.2 %	10.0 %
			0 %		
−10 %	−9.8 %	−9.2 %	−10.0 %	−9.9 %	−10.0 %
−20 %	−19.6 %	−18.5 %	−19.7 %	−19.0 %	−20.2 %

Table 4

Changes in allocation and costs in response to carbon price.

Carbon price (Yuan/t)	60	171	282	393	504
Air frequency	8922	8918	8914	8879	8880
Air passenger (million)	1.205	1.204	1.202	1.198	1.198
HSR frequency	4409	4410	4402	4410	4409
HSR passenger (million)	2.485	2.485	2.488	2.492	2.492
Total cost (billion)	11.509	11.520	11.530	11.541	11.552

Table 5

Changes in allocation and costs in response to HSR price.

HSR price change	Total cost change	Air frequency change	Air passenger change	HSR frequency change	HSR passenger change
+20 %	0.8 %	1.7 %	1.9 %	−0.7 %	−0.9 %
+10 %	0.4 %	1.7 %	1.8 %	−0.8 %	−0.9 %
			0 %		
−10 %	−0.4 %	−5.5 %	−5.8 %	2.6 %	2.8 %
−20 %	−0.9 %	−10.3 %	−10.7 %	5.1 %	5.2 %

Hefei, Guangzhou-Wuxi, and Guiyang-Kunming. By replacing flights with HSR on these short routes, daily emissions across the network can be reduced, yielding significant environmental benefits. As carbon pricing becomes more stringent, the incorporation of HSR on short-haul domestic routes represents an effective strategy for reducing the carbon footprint of intercity travel.

7. Conclusions

The spatial-temporal hierarchical optimisation model of the air-HSR network proposed in this paper is believed to be the first attempt to optimise the intermodal network in both spatial and temporal dimensions, considering environmental impact and social benefit. The multi-objective hierarchical decision-making method proposed by the model extends the application scope and methodology of hierarchical decision-making theory and extends the hierarchical method from top-down or parallel decision-making to the spatial-temporal dimension. By developing a strategic framework that includes both a demand-responsive feedback loop and comparative analyses of passenger cost and emissions reduction objectives, the results of the model provide insights into the nuanced interplay between multimodal connectivity and network performance. Our findings reveal that passenger-centred objectives favour air travel on medium- and long-haul domestic routes, where competitive fares and reduced travel times drive demand. In contrast, an emissions-focused approach emphasises HSR for short- and medium-distance routes, demonstrating its potential as a low-emission alternative to air travel. This shift supports sustainability goals but requires policymakers to address trade-offs in travel time efficiency on certain routes.

The model splits the problem into two hierarchies. In the first hierarchy, the model is designed to find a set of air and HSR routes and frequencies that minimise the emission cost, operational cost, passenger

time cost and fare cost while satisfying the constraints. In an empirical study of a network of all 40 Chinese cities with both air and HSR, there's an increase in the number of flights and a decrease in the number of HSR frequencies, reflecting the large redundancy in the number of seats operated by HSR and the high load factor of flights between major cities in China. Three cities - Yinchuan, Urumqi and Jieyang - have been optimised as not being required to operate HSR for the time being. As a result of the redundancy reduction, daily emission of the air and HSR network between the 40 cities fell from 236 kt to 184 kt, and the total cost fell from 16.97 billion yuan to 12.34 billion yuan per day, from the social welfare perspective.

In the second hierarchy, the air-HSR intermodal nodes left from the first hierarchy are analysed in detail to find the frequency adjustments on the existing timetable in each time window that enables the maximum connections. The results of the first hierarchy of optimisation provide crucial constraints and directions for the second hierarchy while matching the demand and supply on each route to and from each city. After this step, we know at which time each departure/arrival frequency should be adjusted for each city based on the current schedule. Beijing was selected for empirical analysis in this step. It is found that the air and HSR time slot adjustment pattern is related to the time distribution of the connecting flight/HSR, slot capacity, and inbound and outbound demand. In practice, operators could make frequency and time adjustments based on the frequency adjustment results and time allocation results for each time window.

The model's sensitivity analysis on carbon pricing indicates that incremental carbon price increases could promote a modest shift from air to HSR, particularly on short-haul routes, thereby reducing network-wide emissions without requiring extensive HSR capacity expansion. Additionally, the demand-supply feedback loop enables real-time adjustments to service frequencies in response to demand fluctuations, accommodating peak and off-peak travel periods and maintaining network resilience. This adaptability is crucial for avoiding overcapacity or underutilisation in the face of evolving demand patterns.

Further work is necessary to include model refinements, such as setting the value of travel time for different cities according to their income levels and travel purpose distribution, adding other connecting cities besides the current intermodal nodes to the network, as well as adding resilience considerations such as network failure substitution. This hierarchical optimisation model can also be applied to other regional air-HSR intermodal markets for comparative studies.

CRedit authorship contribution statement

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

Declaration of competing interest

The authors declare no conflicts of interest.

Data availability

Data will be made available on request.

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2025-02-01

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<https://doi.org/10.1016/j.jtrangeo.2024.104085>

Lu M, Perez EJ, Mason K, Li MZ. (2025) A hierarchical spatial and temporal optimisation of the air-high speed rail intermodal network. *Journal of Transport Geography*, Volume 123, February 2025, Article number 104085