Intelligent Decision Modeling for Optimizing Railway Cold Chain Service Networks under Uncertainty

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Abstract: Railway cold chain service network design (RCC-SND) aims to optimize the utilization of stations and lines as well as train allocations in a manner that minimizes costs while satisfying the service requirements of shippers. Furthermore, the uncertainties associated with freight demand, transportation costs, quality loss, station handling capacity, and arc capacity make the RCC-SND a complex decision-making problem. To tackle this challenge, we first formulate a Mixed-Integer Nonlinear Programming (MINLP) model to determine hub locations, freight wagon flows, and service frequency. To cope with uncertain parameters with varying degrees of uncertainty incorporated in the model, we extend the problem using fuzzy programming and further convert it to its crisp counterpart. A real-world cases study in Southwest China is performed to validate the proposed model, whose results provide different strategies for decision-makers with varying preferences. There are some main findings: As the number of hubs increases from 5 to 6, a maximum total cost savings of 1.99% can be achieved. Railway operators may opt for different decision preferences, for decisions prioritizing economic efficiency, the cost can decrease by 2.69% compared to deterministic optimization.

Keywords: Railway cold chain, service network design, uncertainty, fuzzy sets, mixed-integer programming

1 Introduction

The cold chain logistics industry in China has experienced substantial expansion, predominantly due to the rapid development of e-commerce and increased consumer demands for fresh and perishable goods. To satisfy the demands of shippers and guarantee the quality of fresh products throughout the entire supply chain, implementing efficient and sustainable cold chain logistics solutions is of essential importance. To maintain a low and constant temperature during transportation and storage, cold chain logistics consumes more fuel and yields more greenhouse gas (GHG) emissions than conventional cargo transport (Li et al., 2022). Given the significant climate change challenge, establishing a low-carbon logistics system becomes imperative. As railway transportation is widely acknowledged for its environmentally friendly attributes compared to other modes such as road and air transport, the utilization of railway cold chain services provides a more effective means of addressing these environmental concerns.

Although railway transportation offers enhanced safety and generates lower CO_2 emissions, punctuality has always been a challenge. To minimize quality losses during the transportation of perishable foods, railway operators favor scheduling direct trains from the loading site to the destination, bypassing the transfer and consolidation of freight wagons at the classification yards to save travel time (Yan et al., 2019; Tang et al., 2021; Li et al., 2023). Point-to-point direct train (PPDT) operations can be implemented where there exists a consistent and sufficient freight demand between origin-destination (OD) stations. In cases where the freight flow between an OD pair does not meet the minimum requirements for operating PPDT, alternative strategies such as step direct trains (SDT) and anti-step direct trains (ASDT) can be used. These strategies are particularly appealing when consolidating freight flows from multiple nearby departure stations to the same destination or when a single departure station has flows to multiple adjacent destinations. Figure 1 depicts the arrangement of PPDT, SDT, and ASDT. Both SDT and ASTDT can help effectively avoid customer attrition due to the insufficient cargo flow to operate direct trains. The transit network comprising PPDT, SDT, and ASDT shares great similarities with a class hub-and-spoke structure, as evidenced by its design.

Currently, two predominant approaches are employed for modeling railway cold chain service networks. The first approach involves strategic planning based on hub-and-spoke network theory. Techniques such as indicator evaluation (Zhang and Liu, 2021) or optimization modeling (Wang, 2018; Lu et al., 2021) are utilized to identify the primary and secondary nodes of the cold chain logistics, However, in these studies, there has been no consideration given to route planning and wagon flow organization. The second method applies modeling techniques traditionally used in railway planning to derive an optimal strategy for wagon flow allocation (Wang, 2008; Liu and Zhang, 2023). While effective in optimizing wagon flows, this approach may easily overlook the specific time-sensitive requirements inherent in cold chain transportation.

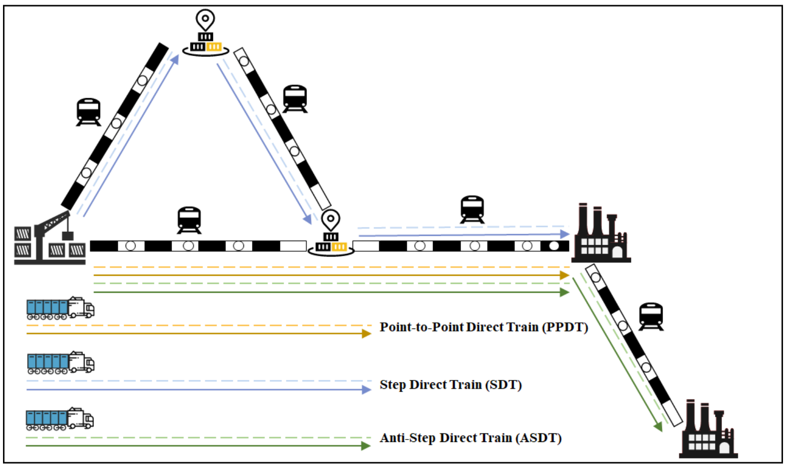

Fig 1. Illustration of PPDT, SDT, and ASDT

Furthermore, a well-designed service network should be able to minimize total costs while, simultaneously, satisfying customer service requirements. Moreover, the network’s robustness and sustainability are of critical importance. In the real world, operating a rail freight system is always uncertain, where numerous factors need to be considered, e.g., fluctuating freight demands (Sayarshad et al., 2010; Milenković et al., 2013), uncertain time (Bababeik et al., 2022), cost variations (Yang et al., 2011), and capabilities (Lai et al., 2008; Sun, 2020a). Three methods can be used to model and tackle the input uncertainty, including stochastic programming, fuzzy programming, and robust optimization (Snyder, 2006). Stochastic programming is a data-dependent method and is commonly used to handle randomness with known probability distribution obtained from historical data, while robust optimization primarily explores the problem's feasibility issue under a certain level of the worst-case scenario. Fuzzy programming typically deals with imperfect data and incomplete knowledge, say, epistemic uncertainty, where a membership function (e.g., triangular fuzzy number, Gaussian fuzzy number, etc.) is derived based on imperfect data combined with the decision-maker's experience to estimate the uncertain parameters (Pedrycz and Gomide, 1998). For RCC-SDN problem, there is usually a lack of sufficient historical data for estimating the uncertain parameters, the use of experience-based fuzzy programming becomes thus appealing to model the uncertain cost-related parameters, energy-related parameters, and quality-loss-related parameters with imperfect or incomplete data. Additionally, as cold chain transportation constitutes a relatively small portion of the entire railway freight sector, the capacity of railway arcs and stations for cold chain is not determined exclusively by their designed capacities and the volume of cold chain cargo. The volume of other cargo types also significantly influences it. In some cases, even though it is impossible to obtain the entire data distribution for these parameters, partial historical data may be available to estimate the distribution of upper and lower bounds. Consequently, in this paper, we need to deal with a mixed uncertainty problem.

In light of the aforementioned considerations, we propose a novel optimization model for an uncertain RCC-SND problem, which simultaneously considers freight demand uncertainty, cost uncertainty, quality-loss-related uncertainty, and capacity uncertainty. Different cost components related to network operations, energy consumption, and cargo loss are calculated. By further considering the constraints imposed by processing capacity, delivery time, and service radius, our approach aims to minimize overall costs while maintaining service quality, fostering an efficient and resilient cold chain logistics system.

Our contribution to the existing literature lies in: (1) proposing a comprehensive railway cold chain service network design model based on the hub-and-spoke framework, integrating the hub selection, freight wagon flow organization, and service frequency determination problems; (2) adopting a fuzzy chance-constraint programming method to deal with mixed uncertainty parameters in RCC-SND problem; (3) comparing with and analyzing three different scenarios representing distinct decision types, which empower railway operators to assess their decisions from both cost and sustainability perspectives. Furthermore, the methodology proposed in this paper are applicable not only to RCC-SDN, but also to other freight service networks characterized by time-sensitive requirements, fixed fleet organization in hub routes, and different types of uncertain parameters. For example, it can be modified for railway express delivery and certain multi-modal express delivery services.

In the subsequent sections, Section 2 provides a review of the literature on railway planning and RCC-SND. Section 3 presents the problem description and formulates the deterministic Mixed Integer Nonlinear Programming (MINLP) and Mixed Integer Linear Programming (MILP) models for the RCC-SND problem. In Section 4, a fuzzy chance-constrained method is employed to reformulate the problem considering uncertain factors. Section 5 gives a case study and discusses managerial implications. Section 6 concludes the study with critical findings.

2 Literature review

2.1 Railway planning

Railway planning can be categorized into three stages: strategic, tactical, and operational. The strategic level includes the construction of physical networks, the procurement of mobile power, and so forth, while the other decisions, e.g., hub location, route planning, service frequency, wagon flow organization (commodity flow optimization), pricing and scheduling are considered at either the tactical or the operational level according to the different decision-making cycles (Crainic, 2000). The boundary between strategic and tactical decisions is sometimes blurred. Some decisions may be considered at different levels based on the problem nature. For instance, the hub location problem can be investigated at either the strategic level or the tactical level depending on whether the infrastructure needs to be built (Archetti et al., 2022). Infrastructure construction is typically excluded in service network design decisions in railway planning, so these decisions are considered under the tactical and operational stages.

There have been numerous studies on the railway freight service network design. Crainic (2000) and Wieberneit (2008) conducted a comprehensive review of the optimization modeling and algorithms for transportation service network design in prior studies. In recent years, significant research efforts have been devoted to various application scenarios, including the optimization of large-scale railway networks (Lin et al., 2012), joint optimization of railway freight considering pricing (Li and Zhang, 2020), and railway express service network planning (Zhou et al., 2022). The railway service network design problem was typically modeled either as a MINLP or as a Mixed Integer Linear Programming (MILP) problem in the literature, where both exact algorithms and approximation algorithms were used to solve the optimization problems.

Railway planning usually entails a significant degree of uncertainty. Consequently, in addition to deterministic models, several studies have delved into stochastic optimization approaches and fuzzy models. The main sources of uncertain factors considered in these studies include freight demand (Sayarshad et al., 2010; Milenković et al., 2013; Cai et al., 2023), capacity (Lin et al., 2022; Yuan et al., 2023), costs (Yang et al., 2017), and time (Bababeik et al., 2022). Several studies investigate the impact brought by multiple sources of uncertainty, i.e., the combination of demand and supply uncertainty (Mohammad and Shafahi, 2017; Sun, 2020b) and the joint capacity and cost uncertainty (Yang et al., 2011). Apart from stochastic optimization and fuzzy approaches, other methods including scenario analysis (Sun, 2020b) and robust optimization (Liu et al., 2014; Rählmann et al., 2021) have also been employed to address the issue of uncertainty. The uncertain parameter types and methods adopted by aforementioned literatures are summarized in Table 1.

Table 1 Review of the representative literatures for railway uncertain optimization

References	Uncertainty parameters				Approaches	Problem
	Freight demand	Capacity	Time	Transport costs		
Sayarshad et al. (2010)	√				Stochastic programming	Rail–car fleet sizing
Milenković et al. (2013)	√				Fuzzy programming	Rail freight car fleet sizing
Cai et al. (2023)	√				Fuzzy programming	Container repositioning
Lin et al. (2022)		√			Fuzzy programming	Path planning problem
Yuan et al. (2023)		√			Stochastic programming	Railcar reallocation optimization
Bababeik et al. (2022)			√		Stochastic programming	Train scheduling
Mohammad and Shafahi (2017)	√	√			Stochastic programming	Path routing
Sun (2020) b	√	√			Fuzzy programming	Path routing
Yang et al. (2011)		√		√	Chance-constrained programming	Path routing, service frequency, freight flow
Liu et al. (2014)	√				Robust optimization	Hub location
Rählmann et al. (2021)	√				Robust optimization	Scheduling
This paper	√	√		√	Chance-constrained programming	Hub location, path routing, service frequency, freight flow

2.2 Cold chain service network design

An efficient and reliable cold chain service network is essential for ensuring the timely and secure delivery of temperature-sensitive products that may deteriorate and become unusable post their shelf life. Osvald and Stirn (2008) explored the impact of perishability as a component of overall distribution costs, focusing on optimizing refrigerated vehicle delivery routes. Golestani et al. (2021) established a model for selecting cold chain hubs with the dual objectives of minimizing overall system costs and maximizing delivered goods' quality. This model incorporates considerations for carbon emission costs, integrating strategic and tactical decisions to determine both hub locations and vehicle routes. Li and Zhou (2021) also adopt a hub-and-spoke model for cold chain hub selection, factoring in carbon emissions, customer satisfaction, construction costs, and operational costs. However, they do not account for vehicle route optimization. In the RCC-SND, the hub-and-spoke model has also been extensively used for hub selection and path planning. As products are collected in hubs, the risk of quality loss during loading and unloading can be reduced. Wang (2018) developed an optimization model for the railway cold-chain logistics network design in China, which determined hub locations, service frequency, and pricing. To optimize the food grain logistics in India, Maiyar et al. (2019a) constructed a hub-and-spoke-based intermodal network. A sustainability analysis was also performed under hub disruption (Maiyar et al., 2019b). Encompassing both primary and secondary hubs, Zhang and Liu (2021) designed a spatial layout scheme for the railway cold chain logistics hub-and-spoke network in China. In addition, research efforts have been given to operational-level decisions, such as the organization of freight wagons (Wang, 2008). In a recent study, Lu et al. (2021) formulated a model to optimize the logistics network of a railway cold chain, which evaluated the influence of several measures such as subsidies and service level improvements on the market share of a railway cold chain.

Even though there are extensive literatures on railway service network design, research on the planning of railway cold chain service networks is noticeably lacking. The existing research of RCC-SND varies in approach. Some studies employ classical logistics network modeling methods, such as multi-layer hub-and-spoke logistics network planning (Wang, 2018; Zhang and Liu, 2021), while others use modeling techniques from traditional railway planning to obtain an optimal wagon flow allocation strategy (Wang, 2008). These approaches often fall short in considering the specific characteristics of railway cold chains. For instance, it's advisable to keep refrigerated wagons separate from other trains due to their stringent timeliness requirements, which mandate the operation of dedicated direct train services. Furthermore, in the optimization of railway cold chains, the energy consumption costs associated with refrigeration are often disregarded. Another crucial aspect to consider is that, compared to general cargo transportation, railway cold chain transportation exhibits higher levels of uncertainty, which stems not only from factors like freight volume and cost parameters but also encompasses uncertainties related to cargo quality losses and refrigeration energy consumption during transit. As previously noted, there is also a notably increased level of uncertainty in capacity. However, railway cold chain planning under uncertain conditions have not been extensively explored.

To address the mixed-uncertainty RCC-SND problem proposed in this paper, we present a three-stage solution, as shown in Figure 2. In the initial phase, a railway topology network is created using geographical information data. The Dijkstra algorithm is adopted to determine the shortest paths between Origin-Destination (OD) nodes, the Kmeans cluster method is employed to obtain the freight demand of cities and establish the city OD freight demand matrix, along with other parameter matrices. In the subsequent step, a mixed-integer nonlinear programming model is introduced, subjected to linearization, and transformed from a fuzzy model to its deterministic counterpart. Moving to the third step, a numerical experiment is executed, and a tuned SCIP solver is applied for resolution.

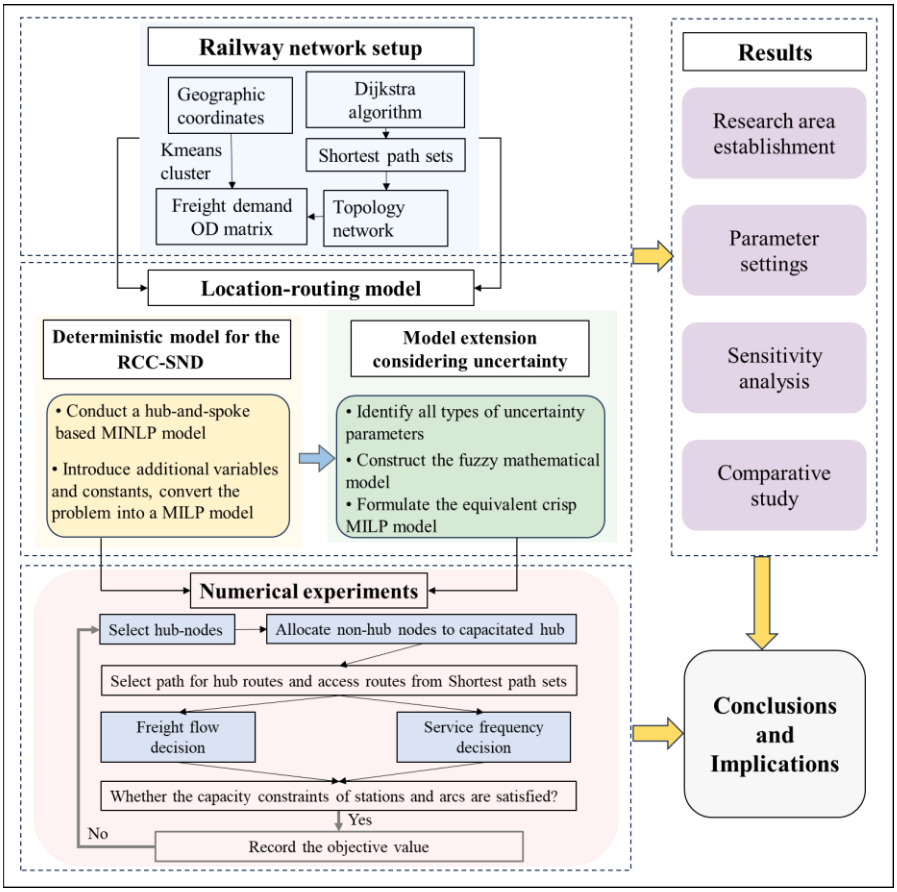

Fig 2. Flowchart of methodology

3 Deterministic model for the RCC-SND

3.1 Problem definition and formulation

We first introduce a deterministic model for the RCC-SND problem, in which all parameters are assumed to be known. Since we conduct the railway service network planning using existing physical infrastructures, hub construction costs are not taken into account. In our model, we consider hub operation costs, transportation costs, cargo quality loss penalties, and fuel costs. The decision-making process involves selecting hub stations and determining the optimal service frequency. The decision period was set to one month in our experiments.

The following are the key assumptions for modeling this problem:

(1) The railway cold chain service network consists of two types of nodes, that is, hub nodes and origin/destination nodes.

(2) A node can belong to only one hub. In the case where nodes a and b both belong to hub c, and $b \in p_{ac\setminus\{a,c\}}$, the train traveling from a to c would have a stopover at node b to pick up the cold chain freight wagons.

(3) Each cargo type q corresponds to a specific freight wagon type v_q.

(4) Between any two nodes, a unique shortest path exists, which can be determined using the Dijkstra algorithm.

(5) Quality degradation of perishable goods occurs only during the transit of railway transportation.

The model's parameters and variables are as follows:

Table 2 Notations

Sets and Indices:	
N	Set of nodes, indexed by i, j, k, l, a;
M	Set of months, indexed by m;
U	Set of fuel types, indexed by u;
Q	Set of cargo types, indexed by q
β_{ij}	Unit linehaul cost per wagon, $CNY/wagon \cdot km$;
α_{kl}	Fixed cost of offering a direct train from hub k to hub l, $Yuan$;
w_{ij}^{q}	Demand of commodity q from node i to node j, accounted by the number of freight wagons;
G_k	The area of hub k ($acre$);
g_k	Unit fixed operation costs of k over the planning period ($CNY/acre$), if node k is selected as a hub;
hc_o	Unit handling cost at origin node ($CNY/wagon$);

hc_d	Unit handling cost at destination node ($CNY/wagon$);
hc_h	Unit handling cost at hubs ($Yuan/wagon$);
t_h^o	Handling time at origin node (h);
t_h^d	Handling time at destination node (h);
t_h^h	Handling time at hub node (h);
t_{ij}	Traveling time from i to j;
ls^q	Unit quality loss penalty cost of commodity q (CNY/ton);
$\varphi(\cdot)$	A function that computes the quality loss of commodities;
s_q	Shelf life of product q (h);
QRP_q	The Quality Reduction Point of cargo q;
D_{ij}	The distance of the shortest path from i to j (km);
$d(a^-, a^+)$	Rail line distance between adjacent nodes a^- and a^+ (km);
LC^{v_q}	The loading capacity of freight wagon v_q (ton);
pr_u	Price of fuel type u;
$c_u^{v_q}$	Traction fuel consumption coefficient of wagon v_q which is powered by locomotive with fuel type u, $kg\ diesel/wagon \cdot km$ or $KWh/wagon \cdot km$;
$cr_{a,del}^{v_q}$	Refrigeration fuel consumption coefficient of wagon v_q with commodity q at arc a, $kg\ diesel/h$;
r_i^u	The percentage of locomotives powered by fuel type u in node i;
C_a	Operation Capacity of arc a;
OC_k	Operation capacity of hub k;
γ	Service radius of hubs;
δ_{ij}^a	If a belongs to the path from i to j, the value is 1, otherwise 0.
y_{kl}	Number of wagons for a direct train in inter-hub routes from hub k to l;
Decision variables:	
x_{kk}	If k is a hub, the value is 1, otherwise, it is 0;

x_{ik}	If node i is assigned to hub k, the value is 1, otherwise, it is 0;
e_{ikl}^{q}	The wagon flow of q from node i to hub l through hub k;
f_{kl}	Service frequency of direct trains from hub k to l;

The objective function aims to minimize the total cost, which includes transportation costs, handling costs, hub operation costs, quality loss penalty, and fuel costs. The cost components are detailed as follows:

Z_1 represents transportation costs, including both hub route costs and access route costs.

$$Z_1 = \sum_{i\in N} \left[\sum_{k\in N} \beta_{ik} D_{ik} \left(\sum_{j\in N} \sum_{q\in Q} w_{ij}^{q} \right) x_{ik} + \sum_{k\in N} \sum_{l\in N} \sum_{q\in Q} \beta_{kl} D_{kl} e_{ikl}^{q} + \sum_{k\in K} \sum_{l\in K} \alpha_{kl} f_{kl} + \sum_{k\in N} \beta_{ki} D_{ki} \left(\sum_{j\in N} \sum_{q\in Q} w_{ji}^{q} \right) x_{ik} \right] \tag{1}$$

Z_2 represents handling costs, which include processing costs at the origin and destination stations, as well as at transfer hubs.

$$Z_2 = \sum_{i\in N} \left[\sum_{j\in N} \sum_{q\in Q} (hc_o + hc_d) w_{ij}^{q} + \sum_{k\in N\setminus\{i\}} \sum_{j\in N} \sum_{q\in Q} hc_h (w_{ij}^{q} + w_{ji}^{q}) x_{ik} \right] \tag{2}$$

Z_3 represents hub operation costs, which are related to the hub's area and the operational cost per unit acre.

$$Z_3 = \sum_{k\in N} g_k G_k x_{kk} \tag{3}$$

Z_4 represents the cost of compensating for cargo quality loss, which depends on the type of cargo and the transportation time.

$$Z_4 = \sum_{i\in N} \sum_{j\in N} \sum_{q\in Q} ls^{q} w_{ij}^{q} LC^{v_q} \varphi\left(\frac{T_{ij}}{s_q}\right) \tag{4}$$

In which, $\varphi(T_{ij}/s_q)$ is a function of the transport time T_{ij}. The shelf life s_q varies depending on the cargo type q, The Quality Reduction Point (QRP_q) represents the threshold of T_{ij}/s_q without any quality deterioration. If $\frac{T_{ij}}{s_q} \leq QRP_q$, there is no degradation in quality. Otherwise, the loss in quality can be measured by Eq. (5).

$$\varphi(T_{ij}/s_q) = \left\{ 0, \frac{\frac{T_{ij}}{s_q} - QRP_q}{1 - QRP_q} \right\}, \forall i, j \in N, q \in Q \tag{5}$$

Energy consumption in the railway cold chain refers to the electricity and other fuels used during storage, transportation, and transshipment. Z_5 and Z_6 represent the energy consumption for locomotive traction and refrigeration, respectively.

$$\begin{aligned} Z_5 = \sum_{i \in N} \Bigg[& \sum_{k \in N} \left(\sum_{j \in N} \sum_{q \in Q} \sum_{u \in U} pr_u c_u^{v_q} r_i^u w_{ij}^q D_{ik} \right) x_{ik} \\ & + \sum_{k \in N} \sum_{l \in N} \sum_{q \in Q} \sum_{u \in U} pr_u c_u^{v_q} r_k^u e_{ikl}^q D_{kl} \\ & + \sum_{k \in N} \left(\sum_{j \in N} \sum_{q \in Q} \sum_{u \in U} pr_u c_u^{v_q} r_j^u w_{ji}^q D_{ki} \right) x_{ik} \Bigg] \end{aligned} \tag{6}$$

$$\begin{aligned} Z_6 = pr_{del} \sum_{i \in N} \Bigg[& \sum_{k \in N} \left(\sum_{j \in N} \sum_{q \in Q} cr_{ik,del}^{v_q} w_{ij}^q t_{ik} \right) x_{ik} \\ & + \sum_{k \in N} \sum_{l \in N} \sum_{q \in Q} cr_{kl,del}^{v_q} e_{ikl}^q t_{kl} \\ & + \sum_{k \in N} \left(\sum_{j \in N} \sum_{q \in Q} cr_{ki,del}^{v_q} w_{ji}^q t_{ki} \right) x_{ik} + \sum_{j \in N} \sum_{q \in Q} (cr_{i,del}^{v_q} t_h^o \\ & + cr_{j,del}^{v_q} t_h^d) w_{ij}^q + \sum_{k \in N \setminus \{i\}} \sum_{j \in N} \sum_{q \in Q} cr_{k,del}^{v_q} t_h^h (w_{ij}^q + w_{ji}^q) x_{ik} \Bigg] \end{aligned} \tag{7}$$

Constraints (8) and (9) guarantee that each node is either selected as a hub or assigned to a hub node. Eq. (10) specifies the number of hubs that can be used in the railway cold chain service network.

$$\sum_{k} x_{ik} = 1, \forall i \in N \tag{8}$$

$$x_{ik} \leq x_{kk}, \forall i, k \in N \tag{9}$$

$$\sum_{k} x_{kk} = H, \forall k \in N \tag{10}$$

Constraint (11) represents the flow balance condition that must be satisfied among the nodes.

$$\sum_{l \in N} \sum_{q \in Q} e_{ikl}^{q} - \sum_{l \in N} \sum_{q \in Q} e_{ilk}^{q} = \left(\sum_{j \in N} \sum_{q \in Q} w_{ij}^{q} \right) x_{ik} - \left(\sum_{j \in N} \sum_{q \in Q} w_{ij}^{q} x_{jk} \right), \forall i, k \in N, q \in Q \tag{11}$$

Constraint (12) determines the frequency when direct train services are available.

$$f_{kl} = \left\lceil \frac{\sum_{i \in N} \sum_{q \in Q} e_{ikl}^{q}}{y_{kl}} \right\rceil, \forall k, l \in N \tag{12}$$

Constraints (13) and (14) are capacity constraints for both the arcs and hub nodes.

$$\sum_{i \in N} \sum_{j \in N} \sum_{k \in N} \sum_{q \in Q} w_{ij}^{q} \delta_{ik}^{a} x_{ik} + w_{ji}^{q} \delta_{ik}^{a} x_{ik} + e_{ikl}^{q} \delta_{kl}^{a} \leq C_a, \forall a \in A \tag{13}$$

$$\sum_{i \in N} \sum_{l \in N \setminus \{k\}} \sum_{q \in Q} e_{ikl}^{q} \leq OC_k, \forall k \in N \tag{14}$$

Constraint (15) ensures that node i must be within the service area of its hub k.

$$x_{ik} \leq \frac{\gamma - D_{ik}}{|\gamma - D_{ik}|} + 1, \forall i, k \in N \tag{15}$$

In constraint (16), T_{ij} represents the time required for goods to travel from node i to node j via hub k and l, which is comprised of the traveling time in hub route (hub node to hub node), the traveling time in access route (hub node to non-hub node), the operation time in origin and destination nodes, and transfer time in hub nodes. T_{ij} should be within the time window of $\underline{T}$.

$$T_{ij} = \sum_{k \in N} \sum_{l \in N} t_{ik} x_{ik} + t_{jl} x_{jl} + t_{kl} x_{ik} x_{jl} + t_h^o + t_h^d + (1 - x_{ii}) t_h^h + \left(1 - x_{jj}\right) t_h^h \leq \underline{T}, \forall i, j, k, l \in N, i \neq j \tag{16}$$

Finally, constraints (15) and (16) define the domains of decision variables

$$x_{ik}, x_{kk} \in \{0,1\}, \forall i, k \in N \tag{17}$$

$$e_{ikl}^{q}, f_{kl} \in N^{+}, \forall i, k, l \in N \tag{18}$$

3.2 Linearization and reformulations

In Section 3.1, a MINLP model has been formulated to address the proposed problem. However, due to the extensive computational requirements for a non-linear optimization problem, a transformation to a linear model becomes appealing. By reformulating the problem into a MILP, we aim to improve the computational efficiency and to better accommodate the parametric uncertainty in the next stage.

3.2.1 Linearizing constraint (12)

The constraint (12) can be reformulated in the following linear form, as shown in constraints (19) and (20).

$$f_{kl} < \frac{\sum_{i \in N} \sum_{q \in Q} e_{ikl}^{q}}{y_{kl}} + 1, \forall k, l \in N \tag{19}$$

$$f_{kl} \geq \frac{\sum_{i \in N} \sum_{q \in Q} e_{ikl}^{q}}{y_{kl}}, \forall k, l \in N \tag{20}$$

3.2.2 Linearizing Z_4

The objective function Z_4 contains a nonlinear term $\varphi\left(\frac{T_{ij}}{s_q}\right)$. To linearize $\varphi\left(\frac{T_{ij}}{s_q}\right)$, we introduce binary variable u_{ij} and a big M parameter. Then, Z_4 is linearized by using constraints (19-23).

$$Z_4 = \sum_{i \in N} \sum_{j \in N} \sum_{q \in Q} ls^q w_{ij}^q LC^v \frac{\frac{T_{ij}}{s_q} - QRP_q}{1 - QRP_q} u_{ij} \tag{21}$$

$$\frac{T_{ij}}{s_q} > QRP_q \cdot u_{ij}, \forall i, j \in N, q \in Q \tag{22}$$

$$\frac{T_{ij}}{s_q} \leq QRP_q\left(1 + M \cdot u_{ij}\right), \forall i, j \in N, q \in Q \tag{23}$$

$$\frac{T_{ij}}{s_q} \leq 1, \forall i, j \in N, q \in Q \tag{24}$$

$$u_{ij} \in \{0,1\}, \forall i, j \in N \tag{25}$$

Then, Z_4 can be expressed by Eq. (26).

$$Z_4 = \sum_{i \in N} \sum_{j \in N} \sum_{q \in Q} ls^q w_{ij}^q LC^v \left(\frac{T_{ij} u_{ij}}{s_q (1 - QRP_q)} - \frac{QRP_q u_{ij}}{1 - QRP_q} \right) \tag{26}$$

However, there is still a nonlinear term $T_{ij}u_{ij}$. Furthermore, it is worth noting that T_{ij} also involves a nonlinear term $x_{ik}x_{jl}$. To solve these problems, we first linearize T_{ij} by introducing binary variables $y_{kl} = x_{ik}x_{jl}$. Consequently, T_{ij} can be converted into the linear form as shown in constraints (27-31).

$$T_{ij} = \sum_{k \in N} \sum_{l \in N} (t_{ik}x_{ik} + t_{jl}x_{jl} + t_{kl}y_{kl}) + t_h^o + t_h^d + (1 - x_{ii})t_h^h + (1 - x_{jj})t_h^h, \forall i, j \in N, i \neq j \tag{27}$$

$$y_{kl} \leq x_{ik}, \forall i, k, l \in N \tag{28}$$

$$y_{kl} \leq x_{jl} \ \forall k, l, j \in N \tag{29}$$

$$y_{kl} \geq x_{ik} + x_{jl} - 1 \ \forall i, j, k, l \in N \tag{30}$$

$$y_{kl} \in \{0,1\}, \forall k, l \in N \tag{31}$$

Then, $T_{ij}u_{ij}$ can be reformulated in Eq. (32).

$$T_{ij}u_{ij} = u_{ij} \left[\sum_{k \in N} \sum_{l \in N} (t_{ik}x_{ik} + t_{jl}x_{jl} + t_{kl}y_{kl}) + t_h^o + t_h^d + (1 - x_{ii})t_h^h + (1 - x_{jj})t_h^h \right], \forall i, j \in N, i \neq j \tag{32}$$

By further introducing binary variables $y_{ijk}^1, y_{ijl}^2, y_{ijkl}^3, y_{ii}^4, y_{jj}^5$, where, $y_{ijk}^1 = u_{ij} \cdot x_{ik}$, $y_{ijl}^2 = u_{ij} \cdot x_{jl}$, $y_{ijkl}^3 = u_{ij} \cdot y_{kl}$, $y_{ii}^4 = u_{ij} \cdot x_{ii}$, $y_{jj}^5 = u_{ij} \cdot x_{jj}$, the reformulated linear formulation of $T_{ij}u_{ij}$ are given in constraints (33-47).

$$T_{ij}u_{ij} = \sum_{k \in N} \sum_{l \in N} (t_{ik}y_{ijk}^1 + t_{jl}y_{ijl}^2 + t_{kl}y_{ijkl}^3) + u_{ij} \cdot t_h^o + u_{ij} \cdot t_h^d + (u_{ij} - y_{ii}^4)t_h^h + (u_{ij} - y_{jj}^5)t_h^h \tag{33}$$

$$y_{ijk}^1 \leq x_{ik}, \forall i, j, k \in N \tag{34}$$

$$y_{ijk}^1 \leq u_{ij}x_{ik}, \forall i, j, k \in N \tag{35}$$

$$y_{ijk}^1 \geq x_{ik} + u_{ij} - 1x_{ik}, \forall i,j,k \in N \tag{36}$$

$$y_{jl}^2 \leq x_{jl} \tag{37}$$

$$y_{ijl}^2 \leq u_{ij}, \forall i,j,l \in N \tag{38}$$

$$y_{ijl}^2 \geq x_{jl} + u_{ij} - 1, \forall i,j,l \in N \tag{39}$$

$$y_{ijkl}^3 \leq y_{kl}, \forall i,j,l \in N \tag{40}$$

$$y_{ijkl}^3 \leq u_{ij}, \forall i,j,k,l \in N \tag{41}$$

$$y_{ijkl}^3 \geq y_{kl} + u_{ij} - 1, \forall i,j,k,l \in N \tag{42}$$

$$y_{ii}^4 \leq x_{ii}, \forall i \in N \tag{43}$$

$$y_{ii}^4 \leq u_{ij}, \forall i,j \in N \tag{44}$$

$$y_{ii}^4 \geq x_{ii} + u_{ij} - 1, \forall i,j \in N \tag{45}$$

$$y_{jj}^5 \leq x_{jj}, \forall j \in N \tag{46}$$

$$y_{jj}^5 \leq u_{ij}, \forall i,j \in N \tag{47}$$

$$y_{jj}^5 \geq x_{jj} + u_{ij} - 1, \forall i,j \in N \tag{48}$$

$$y_{ijk}^1, y_{ijl}^2, y_{ikjl}^3 y_{ii}^4, y_{jj}^5 \in \{0,1\}, \forall i,j,k,l \in N \tag{49}$$

Eventually, Z_4 can be reformulated as follows:

$$\begin{aligned} Z_4 = &\sum_{i\in N} \sum_{j \in N} \sum_{q \in Q} \frac{ls^q w_{ij}^q LC^v}{s_q(1 - QRP_q)} \Bigg(\sum_{k \in N} \sum_{l \in N} (t_{ik} y_{ijk}^1 + t_{jl} y_{ijl}^2 + t_{kl} y_{ijkl}^3) \\ &+ u_{ij} \cdot t_h^o + u_{ij} \cdot t_h^d + (u_{ij} - y_{ii}^4) t_h^h + (u_{ij} - y_{jj}^5) t_h^h \Bigg) \\ &- \sum_{i\in N} \sum_{j \in N} \sum_{q \in Q} \frac{ls^q w_{ij}^q LC^v QRP_q u_{ij}}{1 - QRP_q} \end{aligned} \tag{50}$$

Constrains (22)-(25), (28)-(31), (33)-(49).

4 Model extension considering uncertainty

4.1 Identification of uncertain parameters

In real-world railway cold chain transportation, many parameters, e.g., freight demand and costs, are influenced by market conditions, seasonality, and other factors, resulting in substantial uncertainty. These parameters are represented using triangular fuzzy numbers in this paper. As mentioned before, the carrying capacity and hub operation capacity possess unclear upper and lower bounds for their membership functions, but the distribution can be obtained by using partial historical data. In this paper, we use chance-constraint fuzzy parameters to model this situation (Liu et al., 2003, Yang et al., 2011).. Table 3 displays the uncertain parameters.

Table 3 Uncertain parameters

Triangular fuzzy number	$\widetilde{w_{ij}^{q}}$, $\widetilde{\beta_{ij}}$, $\widetilde{\alpha_{kl}}$, $\widetilde{g_k}$, $\widetilde{hc_o}$, $\widetilde{hc_d}$, $\widetilde{hc_h}$, $\widetilde{c_u^{v_q}}$, $\widetilde{c_{a,del}^{v_q}}$, $\widetilde{QRP_q}$, $\widetilde{y_{kl}}$
Chance-constraint fuzzy parameter	$\widetilde{C_a}$, $\widetilde{OC_k}$

4.2 Chance-constraint fuzzy programming model

The proposed RCC-SND model with uncertain parameters is a chance-constraint fuzzy programming model. In this part, we introduce the method for transforming the model into its corresponding crisp counterpart.

Following is the definition of a general fuzzy optimization problem:

$$f \ = \tilde{C}X \tag{51}$$

$$\tilde{A}X \leq \tilde{B} \tag{52}$$

$$x_j \geq 0, x_j \in X, j = 1,2, \dots, n \tag{53}$$

Where, $\tilde{A}X = \widetilde{A_1}x_1 \oplus \widetilde{A_2}x_2 \oplus \cdots \oplus \widetilde{A_n}x_n$, $\tilde{B} = (\widetilde{b_1}, \widetilde{b_2}, \cdots, \widetilde{b_m})$, $\widetilde{A_j}(j = 1,2,\ldots,n)$ and $\tilde{B}$ are fuzzy sets.

The fuzzy membership function is a function used to quantify the extent to which a number belongs to a fuzzy set N. In fuzzy logic, each element is designated membership values ranging from 0 to 1 to indicate the degree to which they belong to a specific fuzzy set. Eq. (54) is the general representation of fuzzy membership functions:

$$\mu_N(x) = \{F_L\left(\frac{m-x}{a}\right) \quad 1 \quad F_R\left(\frac{x-m}{b}\right) \quad if -\infty < x < m, a > 0 \quad if\ x = m \quad if\ m < x < +\infty, b > 0 \tag{54}$$

When the elements in set a are triangular fuzzy numbers, they are typically expressed as $\tilde{a} = (a^p, a^m, a^o)$. The fuzzy membership function is represented as follows:

$$\mu_a = \{0 \ 1 \ f_a(x) = \frac{x-a^p}{a^m-a^p} \ g_a(x) = \frac{a^p-x}{a^o-a^m} \quad if\ x \le a^p\ or\ x \ge a^o\ if\ x = a^m \quad if a^p \le x \le a^m \quad if\ a^m \le x \le a^o \tag{55}$$

In accordance with Heilpern (1992), the formal definition of the expected interval of a fuzzy number $\tilde{a}$, represented as $EI(\tilde{a})$, is shown in Eq. (56):

$$EI(\tilde{a}) = [E_1^a, E_2^a] = \left[\int_0^1 f_a^{-1}(x)dx, \int_0^1 g_a^{-1}(x)dx\right] = \left[\frac{a^p + a^m}{2}, \frac{a^m + a^o}{2}\right] \tag{56}$$

The expected value of $\tilde{a}$, designated by $EV(\tilde{a})$, can be defined as follows:

$$EV(\tilde{a}) = \frac{E_1^a + E_2^a}{2} = \frac{a^p + 2a^m + a^o}{4} \tag{57}$$

Then, the general fuzzy model given in formulas (51-53) can be converted into a traditional MILP model by employing the methodologies outlined in Liu (2003) and Jiménez et al. (2007). The transformed model is given in formulas (58-61).

$$Min\ f = \sum_{j=1}^{n} c_j^e x_j \tag{58}$$

$$\sum_{j=1}^{n} (\underline{a}_{ij}^s x_j) \le \underline{b}_i^s, i = 1,2,\ldots,m; s = 1,2,..,k \tag{59}$$

$$\sum_{j=1}^{n} \left(\underline{a}_{ij}^s x_j\right) \ge \underline{b}_i^s, i = 1,2,\ldots,m; s = 1,2,..,k \tag{60}$$

$$x_j \geq 0, j = 1,2, \dots, n \tag{61}$$

Where, $c_j^e = EV(\widetilde{c_j})$, $\underline{a_{ij}^s} = sup(a_{ij}^s)$, $\underline{b_i^s} = sup(b_i^s)$, $\underline{a_{ij}^s} = inf(a_{ij}^s)$, $\underline{b_i^s} = inf(b_i^s)$, and k represents k levels of α-cut (for more details, please refer to Mohammadi et al. (2014) and Zhalechian et al. (2016)).

Given the condition that partial historical data is available to estimate the upper and lower bounds of the triangular fuzzy numbers of parameters $\widetilde{C_a}$ and $\widetilde{OC_k}$, we further incorporate the chance-constraint formulation in the fuzzy model. Liu et al. (2003) adopted the chance-constrained programming method to solve the problem, as described in formulas (62-64).

$$f = \tilde{C}X \tag{62}$$

$$\tilde{A}X \leq \tilde{B} \tag{63}$$

$$x_j \geq 0, x_j \in X, j = 1,2, \dots, n \tag{64}$$

Where $\tilde{B} = \left(\widetilde{b_1}, \widetilde{b_2}, \dots, \widetilde{b_m}, \widetilde{b_{m_1}}, \widetilde{b_{m_1+1}^{(p_1)}}, \widetilde{b_{m_1+2}^{(p_2)}}, \dots, \widetilde{b_m^{(p_{m-m_1})}}\right)$. $b_i(t)^{(p_i)} = F_i^{-1}(b_i)$, $F_i(b_i)$ denotes the cumulative distribution function of b_i, while p_i indicates the probability of the violation of constraint i.

Finally, constraints (63-64) can be converted to a linear programming form as follows:

$$Min\ f = \sum_{j=1}^{n} EV(\widetilde{c_j})x_j \tag{65}$$

s.t.

$$\sum_{j=1}^{n} (\underline{a_{ij}^s} x_j) \leq \underline{B_i^s}, i = 1,2, \dots, m; s = 1,2, .., k \tag{66}$$

$$\sum_{j=1}^{n} (\underline{a_{ij}^s} x_j) \geq \underline{B_i^s}, i = 1,2, \dots, m; s = 1,2, .., k \tag{67}$$

Where $\underline{B_i^s}$ and $\underline{B_i^s}$ are given in Eqs. (68) and (69).

$$\underline{B_i^s} = \{\underline{b_i^s}, \quad i = 1,2, \dots, m_1; s = 1,2, \dots, k_1\ \underline{b_i}^{s(p_i)}, \quad i = m_1 + 1, m_1 + 2, \dots, m; s = k_1 + 1, k_1 + 2, \dots, k \tag{68}$$

$$\underline{B}_i^s = \{\underline{b}_i^s, \qquad i = 1,2,\dots,m_1; s = 1,2,\dots,k_1\ \underline{b}_i^{s(p_i)}, \tag{69}$$
$$i = m_1+1, m_1+2,\dots,m; s = k_1+1, k_1+2,\dots,k$$
$$x_j \geq 0, j = 1,2,\dots,n$$

In our paper, to simply the problem, we assume that $\underline{b}_i^{s(p_i)}$ and $\underline{b}_i^{s(p_i)}$ follow normal distributions, whose values can then be obtained by Eqs. (70) and (71). Herein, $\underline{\mu}$ and $\underline{\mu}$ are mean values of $\underline{b}_i^s$ and $\underline{b}_i^s$, and $\underline{\sigma}$ and $\underline{\sigma}$ are the standard deviations.

$$p\left(\underline{b}_i^s\right) = \frac{1}{\sqrt{2\pi}\underline{\sigma}} exp\left\{-\frac{(\underline{b}_i^s-\underline{\mu})^2}{2\underline{\sigma}^2}\right\}, m_1+1, m_1+2,\dots,m; s = k_1+1, k_1+2,\dots,k \tag{70}$$

$$p\left(\underline{b}_i^s\right) = \frac{1}{\sqrt{2\pi}\underline{\sigma}} exp\left\{-\frac{(\underline{b}_i^s-\underline{\mu})^2}{2\underline{\sigma}^2}\right\}, m_1+1, m_1+2,\dots,m; s = k_1+1, k_1+2,\dots,k \tag{71}$$

4.3 The equivalent crisp model

Based on descriptions in Sections 4.1 and 4.2, the equivalent crisp model is given in formulas (72-86). In addition, constraints (8-10), (12), (15-16), (22-25), (28-31), and (34-49) are still held.

$$minZ' = Z'_1 + Z'_2 + Z'_3 + Z'_4 + Z'_5 + Z'_6 \tag{72}$$

$$\begin{aligned} Z'_1 = \sum_{i\in N} \Bigg[&\sum_{k\in K} \beta_{ik}^e D_{ik} \left(\sum_{j\in N}\sum_{q\in Q} w_{ij}^{qe}\right) x_{ik} + \sum_{k\in K}\sum_{l\in K}\sum_{q\in Q} \beta_{kl}^e D_{kl} e_{ikl}^q \\ &+ \sum_{k\in K}\sum_{l\in K} \alpha_{kl}^e f_{kl} + \sum_{k\in K} \beta_{ki}^e D_{ki} \left(\sum_{j\in N}\sum_{q\in Q} w_{ji}^{qe}\right) x_{ik} \Bigg] \end{aligned} \tag{73}$$

$$\begin{aligned} Z'_2 = \sum_{i\in N} \Bigg[&\sum_{j\in N}\sum_{q\in Q} (hc_o^e + hc_d^e) w_{ij}^{qe} + \sum_{k\in K\backslash\{i\}}\sum_{j\in N}\sum_{q\in Q} hc_h^e (w_{ij}^{qe} \\ &+ w_{ji}^{qe}) x_{ik} \Bigg] \end{aligned} \tag{74}$$

$$Z'_3 = \sum_{k\in K} g_k^e G_k x_{kk} \tag{75}$$

$$Z_4' = \sum_{i\in N}\sum_{j\in N}\sum_{q\in Q}\frac{ls^q w_{ij}^{qe} LC^v}{s_q\left(1-QRP_q^e\right)}\left(\sum_{k\in N}\sum_{l\in N}\left(t_{ik}y_{ijk}^1 + t_{jl}y_{ijl}^2 + t_{kl}y_{ijkl}^3\right) + u_{ij}\cdot t_h^o + u_{ij}\cdot t_h^d + \left(u_{ij}-y_{ii}^4\right)t_h^h + \left(u_{ij}-y_{jj}^5\right)t_h^h\right) - \sum_{i\in N}\sum_{j\in N}\sum_{q\in Q}\frac{ls^q w_{ij}^{qe} LC^v QRP_q^e u_{ij}}{1-QRP_q^e} \tag{76}$$

$$Z_5' = \sum_{i\in N}\left[\sum_{k\in K}\left(\sum_{j\in N}\sum_{q\in Q}\sum_{u\in U} pr_u c_u^{v_q e} r_i^u w_{ij}^{qe} D_{ik}\right)x_{ik} + \sum_{k\in K}\sum_{l\in K}\sum_{q\in Q}\sum_{u\in U} pr_u c_u^{v_q e} r_k^u e_{ikl}^q D_{kl} + \sum_{k\in K}\left(\sum_{j\in N}\sum_{q\in Q}\sum_{u\in U} pr_u c_u^{v_q e} r_j^u w_{ji}^{qe} D_{ki}\right)x_{ik}\right] \tag{77}$$

$$Z_6' = pr_{del}\sum_{i\in N}\left[\sum_{k\in K}\left(\sum_{j\in N}\sum_{q\in Q} cr_{ik,del}^{v_q e} w_{ij}^{qe} t_{ik}\right)x_{ik} + \sum_{k\in K}\sum_{l\in K}\sum_{q\in Q} cr_{kl,del}^{v_q e} e_{ikl}^q t_{kl} + \sum_{k\in K}\left(\sum_{j\in N}\sum_{q\in Q} cr_{ki,del}^{v_q e} w_{ji}^{qe} t_{ki}\right)x_{ik} + \sum_{j\in N}\sum_{q\in Q}\left(cr_{i,del}^{v_q e} t_h^o + cr_{j,del}^{v_q e} t_h^d\right)w_{ij}^{qe} + \sum_{k\in K\setminus\{i\}}\sum_{j\in N}\sum_{q\in Q} cr_{k,del}^{v_q e} t_h^h \left(w_{ij}^{qe} + w_{ji}^{qe}\right)x_{ik}\right] \tag{78}$$

s.t.

$$\sum_{l\in N\setminus\{k\}}\sum_{q\in Q} e_{ikl}^q - \sum_{l\in K\setminus\{k\}}\sum_{q\in Q} e_{ilk}^q \le \left(\sum_{j\in N}\sum_{q\in Q}\left(1-\frac{\alpha}{2}\right)\frac{w_{ij}^{qo}+w_{ij}^{qm}}{2} + \frac{\alpha}{2}\cdot\frac{w_{ij}^{qp}+w_{ij}^{qm}}{2}\right)x_{ik} - \sum_{j\in N}\sum_{q\in Q}\left(\left(1-\frac{\alpha}{2}\right)\frac{w_{ij}^{qo}+w_{ij}^{qm}}{2} + \frac{\alpha}{2}\cdot\frac{w_{ij}^{qp}+w_{ij}^{qm}}{2}\right)x_{jk} \tag{79}$$

$$\sum_{l\in N\setminus\{k\}}\sum_{q\in Q} e_{ikl}^{q}-\sum_{l\in K\setminus\{k\}}\sum_{q\in Q} e_{ilk}^{q} \geq \left(\sum_{j\in N}\sum_{q\in Q}\frac{\alpha}{2}\cdot\frac{w_{ij}^{qo}+w_{ij}^{qm}}{2}+\left(1-\frac{\alpha}{2}\right)\frac{w_{ij}^{qp}+w_{ij}^{qm}}{2}\right)x_{ik} - \sum_{j\in N}\sum_{q\in Q}\left(\sum_{j\in N}\sum_{q\in Q}\frac{\alpha}{2}\cdot\frac{w_{ij}^{qo}+w_{ij}^{qm}}{2}+\left(1-\frac{\alpha}{2}\right)\frac{w_{ij}^{qp}+w_{ij}^{qm}}{2}\right)x_{jk} \tag{80}$$

$$f_{kl}<\frac{\sum_{i\in N}\sum_{q\in Q} e_{ikl}^{q}}{\alpha\left(\frac{y_{kl}^{m}+y_{kl}^{o}}{2}\right)+(1-\alpha)\left(\frac{y_{kl}^{p}+y_{kl}^{m}}{2}\right)}+1, \forall k,l\in N \tag{81}$$

$$f_{kl}\geq\frac{\sum_{i\in N}\sum_{q\in Q} e_{ikl}^{q}}{\alpha\left(\frac{y_{kl}^{m}+y_{kl}^{o}}{2}\right)+(1-\alpha)\left(\frac{y_{kl}^{p}+y_{kl}^{m}}{2}\right)}, \forall k,l\in N \tag{82}$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{k\in N}\sum_{q\in Q}\left[\left(sup\left(\left(w_{ij}^{qo}-\alpha\left(w_{ij}^{qo}-w_{ij}^{qm}\right)\right),\left(w_{ij}^{qp}+\alpha\left(w_{ij}^{qm}-w_{ij}^{qp}\right)\right)\right)\right)\delta_{ik}^{a}x_{ik} + \left(sup\left(\left(w_{ji}^{qo}-\alpha\left(w_{ji}^{qo}-w_{ji}^{qm}\right)\right),\left(w_{ji}^{qp}+\alpha(w_{ji}^{qm}-w_{ji}^{qp})\right)\right)\right)\delta_{ik}^{a}x_{ik} + e_{ikl}^{q}\delta_{kl}^{a}\right] \leq sup\left[(C_a^o-\alpha(C_a^o-C_a^m)),\left(C_a^p+\alpha(C_a^m-C_a^p)\right)\right]^{p_i}, \forall a\in A \tag{83}$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{k\in N}\sum_{q\in Q}\left[\left(inf\left(\left(w_{ij}^{qo}-\alpha\left(w_{ij}^{qo}-w_{ij}^{qm}\right)\right),\left(w_{ij}^{qp}+\alpha(w_{ij}^{qm}-w_{ij}^{qp})\right)\right)\right)\delta_{ik}^{a}x_{ik} + \left(inf\left(\left(w_{ji}^{qo}-\alpha\left(w_{ji}^{qo}-w_{ji}^{qm}\right)\right),\left(w_{ji}^{qp}+\alpha(w_{ji}^{qm}-w_{ji}^{qp})\right)\right)\right)\delta_{ik}^{a}x_{ik} + e_{ikl}^{q}\delta_{kl}^{a}\right] \geq inf\left[(C_a^o-\alpha(C_a^o-C_a^m)),\left(C_a^p+\alpha(C_a^m-C_a^p)\right)\right]^{p_i}, \forall a\in A \tag{84}$$

$$\sum_{i\in N}\sum_{l\in N\setminus\{k\}}\sum_{q\in Q} e_{ikl}^{q} \leq sup\left[\left(OC_k^o-\alpha(OC_k^o-OC_k^m)\right),\left(OC_k^p+\alpha\left(OC_k^m-OC_k^p\right)\right)\right]^{p_i}, \forall k\in N \tag{85}$$

$$\sum_{i\in N} \sum_{l\in N\setminus\{k\}} \sum_{q\in Q} e_{ikl}^{q} \geq inf\left[\left(OC_k^o - \alpha(OC_k^o - OC_k^m)\right), \left(OC_k^p + \alpha\left(OC_k^m - OC_k^p\right)\right)\right]^{p_i}, \quad \forall k \in N \tag{86}$$

4.4 Algorithm design

The problem presented in Section 4.3 is a MILP model involving both integer and binary variables. The branch and bound algorithm is an effective exact solution method for solving such problems. It entails relaxing the MILP model into a Linear Programming (LP) model and iteratively dividing the solution space into smaller subspaces. To expedite the solving process, heuristic algorithms are employed to search for improved upper and lower bounds. Cutting techniques are subsequently utilized to prune subspaces unlikely to contain optimal solutions, thereby enhancing the search efficiency. This iterative process continues until a termination condition is reached, such as finding an optimal solution or exploring the entire search space. The process is illustrated in Figure 3.

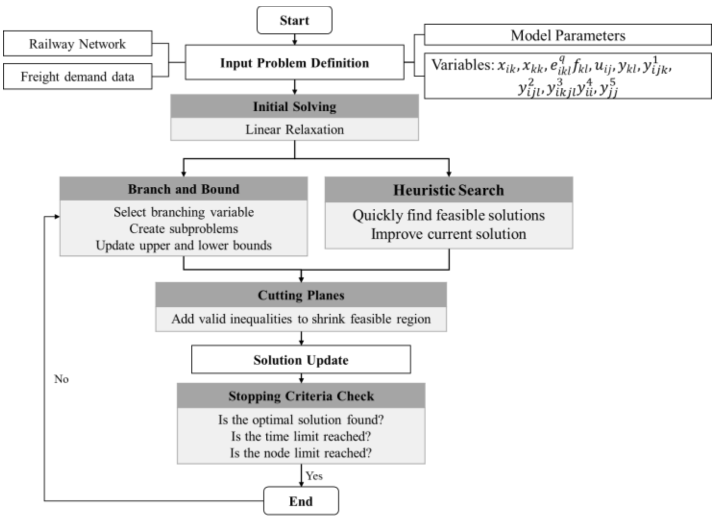

Fig 3. Algorithm design

SCIP is a robust commercial solver designed specifically for solving MILP problems (Gamrath et al., 2020), capable of effectively implementing the aforementioned branch-and-bound, heuristic algorithms, and cutting plane techniques. Before solving, SCIP conducts a series of preprocessing operations on the problem to simplify the problem, reducing the number of variables and constraints, thereby enhancing solving efficiency. These preprocessing operations may entail tasks such as eliminating redundant constraints, fixing specific variable values, merging variables, and more.

Branch-and-Bound serves as the central step in SCIP. It initially relaxes the Integer

Programming (IP) problem into a Linear Programming (LP) problem, selects an integer variable for branching, partitions the domain of that variable into two subsets, and generates two new subproblems accordingly. Subsequently, SCIP solves these subproblems and updates the current known optimal solution (upper bound and lower bound). This iterative process continues until the optimal solution is identified or a termination condition is satisfied. During this process, SCIP also employs various heuristic search strategies to accelerate the solving process. Heuristic search enables the rapid identification of feasible solutions or approximate optimal solutions.

In practical applications, SCIP's solving speed can be very slow due to the dimensional explosion caused by the excessive number of variables and parameters. Fortunately, SCIP 7.0 offers adjustable parameters, allowing users to fine-tune the default settings to solve problem instances to optimality as quickly as possible. SCIP 7.0 provides 2605 parameters, each with at least two possible values, resulting in at least 2^{2605} combinations-a massive number. Therefore, it is practically impossible to test all combinations to find the best performance.

In this study, we focus on tuning three important "meta-parameters" in SCIP: presolving, primal heuristics, and cuts. Each of them has four possible settings: default, off, aggressive, and fast, so it's $4^3 = 64$ combinations. Our goal is to find the setting from these 64 combinations that produces the best average primal-dual gap in the shortest possible time.

5 Numerical experiments

5.1 Research area

In this numerical study, we focus on four provincial-level administrative regions in Southwest China (Sichuan, Chongqing, Guizhou, and Yunnan). Based on current statistics, Sichuan Province has 95 railway freight stations with cold chain business, Guizhou has 62, Chongqing Municipality has 54, and Yunnan Province has 64. As station-to-station freight demand falls short of meeting the requirements for forming railway freight trains, consolidating dispersed railway freight demands from various stations and organizing train transportation based on cities can effectively shorten mainline transportation time and enhance railway transportation efficiency. Hence, in this section, we cluster the freight stations and identify the most suitable station as the distribution center among multiple freight stations.

K-means is an unsupervised clustering method that groups similar objects together to reveal the structure and patterns of data. Due to its simplicity and efficiency, it finds wide application in logistics demand clustering. The method entails specifying the number of clusters k and initializing cluster centers for each cluster. Through iterative processes of reselecting cluster centers and dividing clusters to optimize intra-cluster distance, it progresses until achieving the optimal solution or meeting stopping criteria. Within the scope of this study, 21 cities have opened railway cold chain transportation. Consequently, we set the number of clusters K = 21 and randomly initialize cluster centers for each cluster. Figure 4 illustrates the results of K-means clustering, where 21 cluster centers represent the distribution centers of 21 cities respectively.

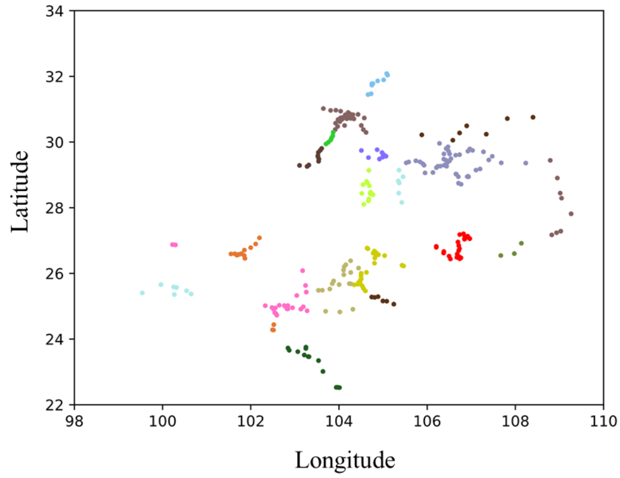

Fig.4 Locations of the railway station clusters

Figure 5 shows the locations of the cluster centers in the cities and the railway connections between these cities.

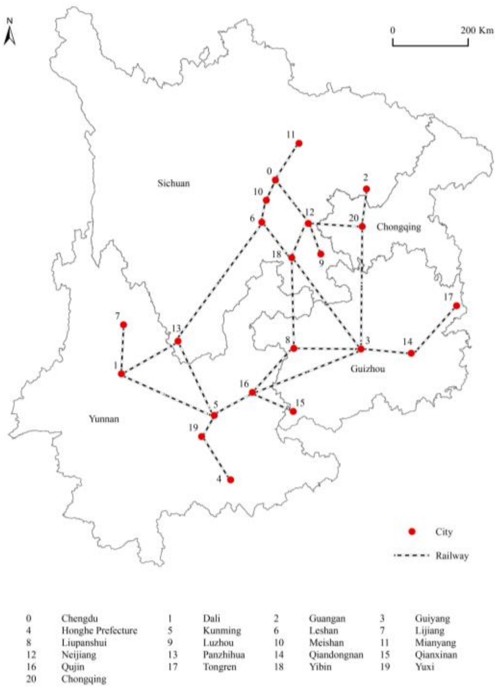

Fig. 5 The research area and the railway network

5.2 Parameters

Referring to Lai and Hwang (1992), the initial step in generating the triangular fuzzy parameters to determine the most likely value (a^m), the most pessimistic value (a^p), and the most optimistic value (a^o). In our paper, we first randomly generated the most likely value a^m from uniform intervals, as Table 4 shows. Subsequently, Eq. (82) was used to generate a^p and a^o from the most likely value, where r_1 and r_2 were randomly generated from a uniform distribution between 0.2 and 0.8.

$$a^p = (1 - r_1)a^m;\ a^o = (1 + r_2)a^m \tag{82}$$

The freight flow statistics between cities is obtained from a professional transportation company in command of the entire RCCT system in China (https://www.crscl.com.cn/). The most likely value (a^m) for some cost-related and facility-related uncertain parameters based on survey to the railway transportation decision-makers. Based on the actual commodities transited by RCCT in China and the transportation temperature requirements, we divide the cargo into 5 categories: fresh vegetables, fresh fruits, frozen aquatic products, frozen meat, as well as milk. In this paper, the shelf life of fresh vegetables, fresh fruits, frozen aquatic products, frozen meat, milk takes 144h, 144h, 432h, 432h, 288h respectively.

Table 4 Parameters' value

Parameter	Value	Parameter	Value
N	21	ls^1	100
H	H=5 for problem 1,	ls^2	100
	H=6 for problem 2	ls^3	100
β_{ij}	~uniform (4, 6)	ls^4	100
α_{kl}	~uniform (60000, 80000)	ls^5	100
hc_o	~uniform (80, 100)	s^1	144
hc_d	~uniform (80, 100)	s^2	144
hc_h	~uniform (30, 50)	s^3	432
g_k	~uniform (500, 700)	s^4	432
$c_{ele}^{v_1}$	~uniform (200, 250)	s^5	288
$c_{ele}^{v_2}$	~uniform (200, 250)	pr_{del}	9
$c_{ele}^{v_3}$	~uniform (300, 350)	pr_{ele}	0.5
$c_{ele}^{v_4}$	~uniform (300, 350)	t_h^o	6
$c_{ele}^{v_5}$	~uniform (250, 300)	t_h^d	6
$c_{del}^{v_1}$	~uniform (60, 80)	t_h^h	2
$c_{del}^{v_2}$	~uniform (60, 80)	LC^{v_1}	21.25
$c_{del}^{v_3}$	~uniform (80, 100)	LC^{v_2}	21.25
$c_{del}^{v_4}$	~uniform (80, 100)	LC^{v_3}	29.44
$c_{del}^{v_5}$	~uniform (70, 90)	LC^{v_4}	29.44
$\widetilde{cr}_{a,del}^{v_1}$	~uniform (100, 150)	LC^{v_5}	26.82
$cr_{a,del}^{v_2}$	~uniform (100, 150)		
$cr_{a,del}^{v_3}$	~uniform (350, 450)		
$cr_{a,del}^{v_4}$	~uniform (350, 450)		
$cr_{a,del}^{v_5}$	~uniform (250, 350)		
QRP_q	~uniform (0.4, 0.6)		
y_{kl}	~uniform (20, 30)		

To evaluate the performance of SCIP on the problem presented in this paper, we use the deterministic optimization scenario with H=5 as an example. When H=5, using the default SCIP settings, the presolving phase deletes 395,151 variables and 5,664 constraints while adding 8,569 constraints, resulting in a total of 14,140 variables and 9,254 constraints post-presolving. During the branch-and-bound phase, 301,739 branch nodes are generated, and the optimal solution is obtained in 9,344 seconds.

By adjusting the parameters, we record the time taken for each parameter combination to achieve the best primal-dual gap. The parameter combination resulting in the shortest solving time is applied to all subsequent numerical experiments. Figure 6 compares the performance of SCIP with default parameters and with tuned parameters in solving the deterministic model with H=5.

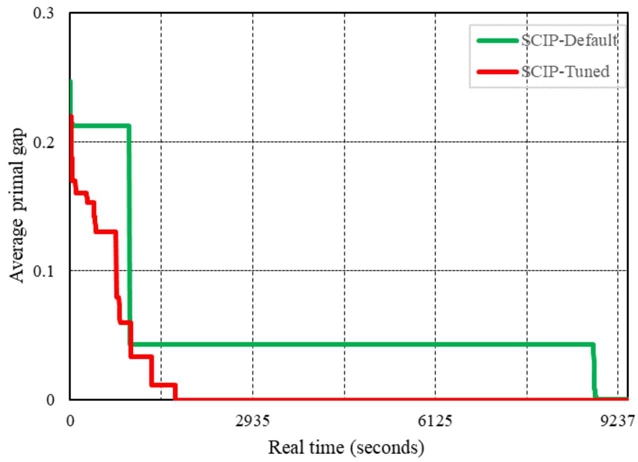

Fig.6 Average primal gap achieved by various algorithms as a function of running time

5.3 Experimental results

5.3.1 Sensitivity analysis

The results of cases for H=5 and H=6 with varying values of p_i ($p_i = 0.05, 0.1$) and α ($\alpha = 0.1$-0.9) are shown in Tables 5 and 6. It can be seen that a better cost performance can be achieved with a compromise of the feasibility of the solutions. In this regard, decision-makers need to consider the trade-off between the potential cost reduction and the demand fulfillment rate of the railway cold chain network. To address this particular issue, Jiménez et al. (2007) developed a method, wherein the objective is represented as a fuzzy set $\widetilde{W}$. $\underline{W}$ is the target optimal value, the decision maker will be completely satisfied if $Z < \underline{W}$. $\underline{W}$ represents the decision maker's tolerance threshold, if $Z > \underline{W}$, the results cannot be accepted. The membership function of $\widetilde{W}$ is then given in Eq. (83).

$$\mu_{\widetilde{W}}(Z) = \{1, \quad if\ Z < \underline{W}\ \frac{\underline{W} - Z}{\underline{W} - \underline{W}}, \quad if\ \underline{W} \leq Z \leq \underline{W}\ 0, \quad if\ Z > \underline{W} \tag{83}$$

Subsequently, an index $R_{\widetilde{W}}(Z^0(\alpha))$ proposed by Yager (1979) was adopted to evaluate the satisfaction degree of fuzzy number $Z^0(\alpha_k)$ to fuzzy set $\widetilde{W}$ (for more details, refer to Jiménez et al. (2007)).

$$R_{\widetilde{W}}(Z^0(\alpha)) = \frac{\int_{-\infty}^{+\infty} \mu_{\tilde{Z}^0(\alpha)}(Z) \cdot \mu_{\widetilde{W}}(Z)dZ}{\int_{-\infty}^{+\infty} \mu_{\tilde{Z}^0(\alpha)}(Z)dZ} \tag{84}$$

Then, the fuzzy decision $\tilde{F}$ is defined in Eq. (85).

$$\mu_{\tilde{F}}(x(\alpha_k)) = \alpha_k * R_{\widetilde{W}}\left(\tilde{Z}^0(\alpha_k)\right) \tag{85}$$

Ultimately, the crisp decision x^* can be derived by the following equation (86):

$$\mu_{\tilde{F}}(x^*) = \left\{\alpha_k * R_{\widetilde{W}}\left(\tilde{Z}^0(\alpha_k)\right)\right\} \tag{86}$$

In our paper, the uncertain parameters in objective functions are converted into their expected values in the crisp model. That means, for each certain α value, $\mu_{\tilde{Z}^0(\alpha)}(Z) = 1$, and $R_{\widetilde{W}}(Z^0(\alpha))$ is equal to $\mu_{\widetilde{W}}(Z)$, then, the crisp decision x^* can be derived by Eq. (87).

$$\mu_{\tilde{F}}(x^*) = \{\alpha_k * \mu_{\widetilde{W}}(Z(\alpha_k))\} \tag{87}$$

Table 5 Optimal solution of problem 1 (H=5)

	$p_i = 0.05$					$p_i = 0.1$				
α	Z	Z1	Z2	Z3	$\mu_{\widetilde{W}}(z)$	Z	Z1	Z2	Z3	$\mu_{\widetilde{W}}(z)$
0.1	8163.56	7736.632	110.751	316.177	1	8071.947	7645.09	109.077	317.78	1
0.2	8185.044	7754.144	112.975	317.925	0.857	8079.733	7648.087	115.761	315.885	0.921
0.3	8230.607	7798.446	113.55	318.611	0.556	8078.455	7649.088	115.587	313.78	0.934
0.4	8232.788	7800.476	114.776	317.536	0.541	8150.038	7718.851	114.784	316.403	0.206
0.5	8285.02	7852.073	114.479	318.468	0.196	8158.191	7719.431	119.84	318.92	0.123
0.6	8292.238	7858.045	115.751	318.442	0.148	8150.496	7722.619	110.594	317.283	0.201
0.7	8298.503	7863.309	116.799	318.395	0.106	8162.22	7727.327	116.003	318.89	0.082
0.8	8313.202	7882.137	112.667	318.398	0.009	8162.73	7733.31	110.799	318.621	0.077
0.9	8314.538	7885.31	110.888	318.34	0	8170.303	7737.436	114.116	318.751	0

Table 6 Optimal solution of problem 2 (H=6)

	p=0.05					p=0.1				
α	Z	Z1	Z2	Z3	$\mu_{\widetilde{W}}(z)$	Z	Z1	Z2	Z3	$\mu_{\widetilde{W}}(z)$

0.1	8096.182	7673.816	112.687	309.679	1	8044.443	7620.993	113.269	310.181	1
0.2	8097.462	7677.746	110.072	309.644	0.978	8047.172	7622.993	114.177	310.002	0.963
0.3	8098.8	7679.327	109.86	309.613	0.955	8050.659	7626.452	114.519	309.688	0.916
0.4	8099.759	7682.916	107.615	309.228	0.939	8094.288	7673.816	110.793	309.679	0.328
0.5	8101.17	7685.723	106.435	309.012	0.914	8098.596	7678.331	110.967	309.298	0.270
0.6	8106.793	7688.603	109.198	308.992	0.818	8106.947	7686.376	111.414	309.157	0.158
0.7	8121.207	7702.603	109.868	308.736	0.571	8110.373	7689.773	111.668	308.932	0.111
0.8	8130.177	7713.414	108.147	308.616	0.417	8111.857	7694.713	108.285	308.859	0.091
0.9	8154.462	7739.061	106.912	308.489	0	8118.645	7702.603	107.427	308.615	0

Tables 7 and 8 show the membership degree for each α-acceptable optimal solution to $\tilde{F}$.

Table 7 Membership degree of optimal solutions for problem 1 (H=5)

	α_k	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
p_i =0.05	$\mu_{\tilde{F}}(x(\alpha_k)$	0.1	0.172	0.167	0.217	0.098	0.089	0.074	0.007	0
p_i =0.1	$\mu_{\tilde{F}}(x(\alpha_k)$	0.1	0.184	0.28	0.082	0.064	0.121	0.058	0.062	0

Table 8 Membership degree of optimal solutions for problem 2 (H=6)

	α_k	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
p_i =0.05	$\mu_{\tilde{F}}(x(\alpha_k))$	0.1	0.196	0.287	0.375	0.457	0.491	0.399	0.333	0
p_i =0.1	$\mu_{\tilde{F}}(x(\alpha_k))$	0.1	0.195	0.275	0.131	0.135	0.095	0.078	0.073	0

The optimal solution, according to Eq. (87), should be the one with the highest degree of membership. Table 7 illustrates that for p_i =0.05. In this case, the 0.4-feasible exhibits the highest membership degree, with the objective value of 8232.788. While for p_i =0.1, the 0.3-feasible optimal solution exhibits the highest degree of membership, with the objective value of 8078.455. Even though the latter option seems more appealing compared to p_i =0.05 in terms of cost effectiveness, it is, however, accompanied with a compromise of the feasibility of constraints.

If decision-makers prefer conservative or risk-averse options, the solution with p_i =0.05 is more attractive. Conversely, if they prioritize economic performance with the tolerance of a certain level of reduced service level and demand fulfillment rate, they would opt for p_i =0.1. Similarly, as Table 8 shows, in the case where H=6, the conservative choice would be p_i=0.05, α=0.6, Z=8106.793, while the economic-preferred choice would be p_i=0.1, α=0.3, Z=8050.659. Furthermore, if these solutions are found unsatisfactory, decision-makers can modify the goal and tolerance thresholds or refine the feasibility degrees to obtain more appropriate solutions.

5.3.2 Comparative study

Table 9 presents the optimization outcomes for three distinct preferences, namely Deterministic optimization (S1), Conservative Uncertain Optimization (S2), and Economic Uncertain Optimization (S3), in the cases of H=5 and H=6. For which, S1 means all the parameters be fixed value and all constraints be met strictly, S2 picks p_i =0.05, α =0.4 for H=5 and p_i=0.05, α=0.6 for H=6, S3 picks p_i =0.1, α =0.3 for H=5 and p_i=0.1, α=0.3 for H=6. Regardless of the number of hubs, it is evident that the total cost of deterministic optimization is the highest, followed by S2, while the cost of S3 is the most favorable. This observation is based on a simple reason: deterministic optimization fixes parameters rigidly and requires all constraints to be met strictly, resulting in higher costs, whereas uncertain optimization adopts a more flexible approach, relaxing non-rigid constraints and exploring a broader solution space to achieve more optimal results. Moreover, in practical situations, parameters like railway operating costs, freight demand, hub processing capacity, and arc pass-through capacity are hardly to be fixed constant. Uncertain optimization takes this into account when modelling the service network design, enabling the optimization results to be more practical and applicable to real-world situations.

Table 9 Optimal costs for cases of H=5 and H=6 with three decision preference

hubs	Scenarios	Total costs	Hub route costs	Access route costs	Handlin g costs	Fixed operating costs of hubs	Fuel costs	Quality loss penalty cost
H=5	S1	8302.055	4638.291	2714.955	163.500	356.937	312.452	115.92

H=5	S2	8232.788	4213.691	2996.700	175.500	414.585	317.536	114.776
H=5	S3	8078.455	4281.001	2784.250	170.700	413.137	313.780	115.587
H=6	S1	8136.826	4872.78	2287.358	167.340	391.258	303.218	114.872
H=6	S2	8106.793	4711.140	2310.542	176.620	490.301	308.992	109.198
H=6	S3	8050.659	4505.916	2496.431	174.54	449.565	309.688	114.519

Notably, the total cost for H=6 is always less than H=5 for any decision preference. To determine the reasons, we analyze all components that constitute the total cost. The 'Hub route cost' in Table 8 represents the fixed and variable costs of operating direct trains between two hubs, which are primarily influenced by the frequency of train operations. The Hub route costs for H=6 is evidently higher than that for H=5. This is due to the positive correlation between the number of hubs and the direct train services connecting the hubs. Figure 7 illustrates the frequency of direct train services in different scenarios. It can be observed that the addition of a hub necessitates the operation of 7-16 additional direct trains, consequently resulting in a substantial increase in bub route costs. The 'Access route cost' accounts for the transportation costs between hub nodes and non-hub nodes, which depends on the freight volume and access route distance. In contrast to the bub route costs, it is seen that the access route costs drop as the number of hubs increases. This phenomenon occurs due to the reduction in distance between non-hub nodes and hub nodes, leading to a decrease in consolidation costs. And the costs reduction in the access routes is rather greater than the costs increase in hub routes. The 'Handling costs' encompass the expenses associated with handling goods at the origin, destination, and hub stations, including loading, unloading, transfer, packaging and repackaging (if necessary). The handling costs increase as the number of hubs rises, but the increase is not significant. The 'Fixed operating costs of hubs' refers to the fixed operational expenses of the hub stations, which are directly proportional to the hubs' areas. Clearly, as the number of hubs rises, so will their fixed operating costs. Lastly, 'Quality loss penalty costs' denotes the recompense provided by rail operators to shippers in the event of cargo deterioration. With the number of hubs rises, the quality loss penalty cost decreases. This occurs because the more hubs shorten distance and time for stations to reach their hubs, consequently lowering the risk of quality deterioration.

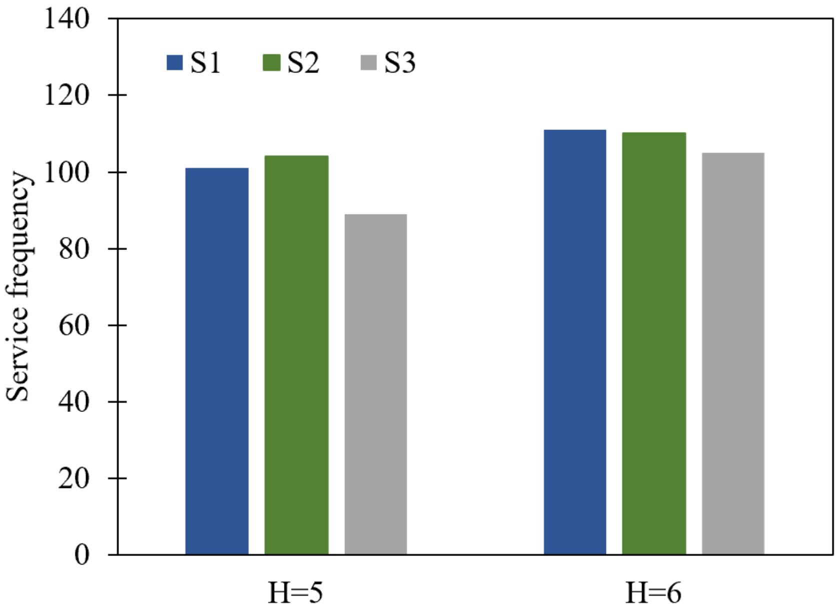

Fig. 7 Service frequency of direct trains for cases of H=5 and H=6 with three decision preference

Figure 8 depicts the optimal scheme of service network for the above-mentioned instances. The thickness of solid lines indicates the service frequency of direct trains in hub routes, while the dashed lines represent access routes. It can be seen that nodes 3, 5, and 18 are always selected as hubs for the three decision-making scenarios of S1, S2 and S3, regardless of the number of hubs. The service frequency of direct trains between 0-5 or 18-5 is the highest, indicating that freight volume heavily influences the selection of hub nodes. However, it is important to note that freight volume is not the sole determinant, optimal designs often prioritize hubs with shorter inter-hub distances, nodes in remote areas (such as 1, 2, 4, 7, 11, 17) are never selected as hubs because they may increase hub route costs. It can be seen that the hub route costs are the highest for S1, regardless of the number of hubs, however, the access route costs are lowest for S1. This indicates that under more stringent constraints, the algorithm tends to operate more direct train services between hubs (as Figure 5 shows), thus avoiding the risk of overloading a specific route with excessive freight volume or causing capacity shortages at a particular hub.

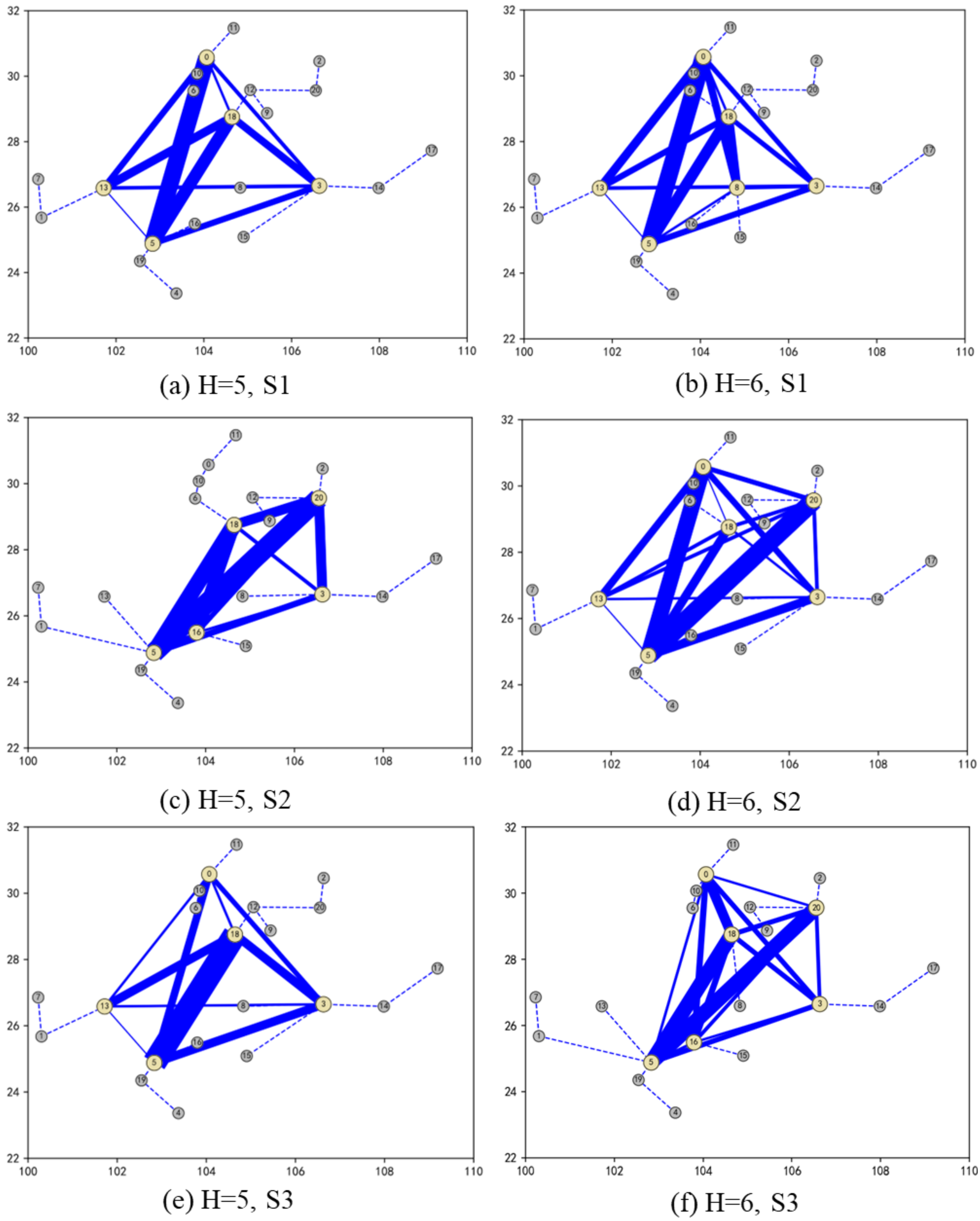

Fig. 8 Illustration of optimal solutions

6 Conclusions

This paper makes two major contributions to the literature. First, we proposed a new MINLP model for the sustainable RCC-SND problem to determine hub selection, service frequency, and freight wagon flows by simultaneously taking into account operation costs, quality loss penalty costs, and energy costs. The objective is to obtain an optimal service network that minimizes total costs while meeting capacity constraints and satisfying the service level requirements of shippers; Second, we further developed the model using a chance-constraint fuzzy programming model to analyze the impact of the uncertainty related to freight demand, cost-related parameters, quality-loss related parameters, and capacity-related parameters. By leveraging a hybrid approach to deal with different parametric uncertainty, the proposed model becomes more robust and adaptable to real-world scenarios.

We showed the application of the proposed method with numerical experiments, specifically, concentrating on four provincial-level administrative regions in Southwest China (Sichuan, Chongqing, Guizhou, Yunnan). In addition, a number of sensitivity analyses were conducted, and the management insights were extensively discussed.

In practice, railway operators can assess their decisions from both cost and sustainability perspectives. Networks that favor more cost-effectiveness usually have a greater risk of violating capacity and reduced demand fulfillment rate. The results demonstrated that the fuzzy approach has a significant influence on the RCC-SDN. Regardless of the number of hubs, S1 has the highest total cost, followed by S2, while the cost of S3 is the most favorable. Decision-makers who pursue more cost-effective options run a greater risk of violating capacity constraints and confront greater uncertainty regarding demand, cost and quality loss. Additionally, the increase of hub number has a significant impact on the total costs, as the number of hubs increases from 5 to 6, a maximum total cost savings of 1.99% can be achieved. As it reduces the cargo consolidation costs in access route, and the increased service frequency of direct train reduces the waiting time of cargos, thereby reducing the quality loss.

Furthermore, the service network design approach proposed in this paper are applicable not only to railway cold chains but also to other freight service networks characterized by time-sensitive demands and fixed fleets. For instance, it can be adapted for railway express delivery, which, like railway cold chains, necessitates organized train services and time-sensitive requirements. Certain express delivery operations, for instance, require the organization of dedicated dispatch fleets and adhere to stringent time constraints. Nevertheless, there are some limitations to the model's applicability, as decision-makers may have preferences beyond economic considerations. Future research could explore the following directions: (1) Designing service networks with a focus on the interests of both railway operators and shippers, minimizing the operational costs for railway operators while maximizing the quality of goods; (2) Incorporating shipper preferences into the modeling process, utilizing historical data analysis to capture shipper preferences regarding time, cost, and other factors.

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Statements & Declarations

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Competing Interests

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Ethics approval

Not applicable

Consent to participate

All authors agree to participation.

Consent for publication

Not applicable