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Integrated multimodal freight service network design and pricing with a competing service integrator and heterogeneous shipper classes

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ABSTRACT

In recent years, the highly fragmented multimodal transport offer in several countries has required the integration of these services by logistics service integrators (LSIs). The challenge for LSIs is to set up multimodal transport corridors that can respond efficiently to the heterogeneous demand of shippers and that are cost- and price-competitive against other transport solutions. We develop a bi-level programming model to assess the corridor's pricing and the service network design simultaneously. In the upper level, the model maximizes the profit of the LSI by designing the service network and implementing shipment-based pricing for paths adapted to the heterogeneous demand for transport services. In the lower level, the total cost of shippers in the network who choose services according to their preferences is minimized. We solve the model using reformulation and linearization techniques. Computational experiments based on the real-world case of the New Western Land-Sea Corridor in China are conducted to demonstrate the proposed model and to draw managerial insights. The results show that the shipment-based pricing strategy is beneficial for the LSI to obtain profit increases when considering the shippers' heterogeneous preferences on time and reliability. The results also revealed that the service design and pricing decisions of the LSI are not only related to operational costs but also depend on the competitors' offers in the market. Moreover, the impact of the level of frequency discretization, waiting time cost, the penalty cost for not fully utilized services, and the generalized cost of the no-purchase option on the decisions of the LSI are also investigated in the sensitivity analysis.

1. Introduction

The role of multimodal transport has become more and more vital in reducing costs and negative effects of trucking in several inland container supply chains (Yin et al., 2021). At the same time, multimodal transport services suffer from a general lack of integration and synchronization, with a rather fragmented offer (Khakdaman et al., 2020). For this reason, in recent years, an increasing number of logistics service providers have integrated the service capabilities of different multimodal transport services and provide customized services to shippers in the container multimodal transport market (Lam and Gu, 2016; Tavasszy et al., 2017; Khakdaman et al., 2020; Pfoser et al., 2021). These are usually referred to as logistics service integrators (LSIs). For example, as an advanced logistics company in China, Cainiao does many logistics services integration and creates an efficient logistics and distribution system (Wang et al., 2022a).

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For an LSI, service network design and pricing decisions are crucial to guarantee competitiveness as the price, and the service design affect attractiveness to shippers (Khakdaman et al., 2020). The LSI also face a significant challenge in optimizing pricing and service operations since they simultaneously influence each other. Specifically, the pricing of the service needs to be profitable for the LSI and maintain a certain level of low price to capture the goal users. Precise cost estimates for service operations based on the different preferences of shippers and an evaluation of the competitors in the market are significant conditions to maintain this balance (Tawfik and Limbourg, 2018; Duan et al., 2019).

This paper considers a joint service network design and pricing problem (JSNDPP) from the view of the LSI at a tactical level. Given a set of requirements from a shipper set with heterogeneous preferences featuring origins and destinations, demand, and delivery time limitations, as well as a multimodal network where transport services are activated, an LSI decides the transport paths, service frequency, and end-use price jointly to service demands. In addition, we consider the value of time and reliability to describe shippers' preferences. To simulate a competitive environment, we consider a slower but cheaper service alternative and the no-purchase option for customers to exit the market; as seen in Paneque et al. (2021).

The joint tactical service network design and pricing problem in freight transport has received some attention. Still, previous research has mainly focused on a single mode of transport; see for example, Brotcorne et al. (2008) and Berling and Eng-Larsson (2016). Among the few studies on the JSNDPP that have considered a multimodal freight transport network, Ypsilantis and Zuidwijk (2013) proposed a model for a maritime terminal operator to maximize the profits by optimizing the price and the multimodal service network at the same time. Tawfik and Limbourg (2019) developed a path-based multicommodity formulation from the perspective of an intermodal operator to design freight services and determine their associated prices. However, these studies tackled an arc-based pricing problem, which is limiting since shippers do not combine transport legs themselves. Instead, they are typically offered complete transport options from origin to destination. Therefore they do not allow the service integration problem of the LSI to be studied sufficiently. Also, they did not consider the value of time and reliability from the perspective of the shippers, which is relevant when making network design trade-offs. Finally, competition is typically modeled as an expensive all-road alternative. In contrast, we consider a more challenging cheaper, and slower alternative as a possible service substitution because this kind of alternative can potentially reduce the market shares of the corridor operated by the LSI.

We model the described problem through a novel non-linear bi-level service network design and pricing model. To solve the model, we convert it into a one-level MILP by utilizing primal–dual optimality conditions for the replacement of the lower level and using linearization methods such that a standard branch-and-bound algorithm can easily solve it. To validate our model, we use data from the New Western Land-sea Corridor in China. The experiments and sensitivity analysis aim to derive managerial implications, particularly concerning guidelines for enhancing the LSI's competitive status in the freight market.

The contribution of this study is three-fold. First, a bi-level model is proposed to investigate the joint path-based pricing and service network design problem in the context of the multimodal multi-user-class freight transportation system, where shippers have heterogeneous preferences through their Value of Time (VOT) and Value of Reliability (VOR). Second, the bi-level model considers a competitor providing cheaper and slower transport alternative options from the perspective of the LSI in the upper level, and the effect of endogenous waiting time caused by frequency delay from the perspective of shippers in the lower level. Third, we conduct the primal–dual optimality conditions and linearization methods to reformulate the above model as a single-level mixed-integer linear program (MILP) that allows the globally optimal solution of the proposed bi-level model to be obtained using existing algorithms in commercial software packages. We also conduct a series of numerical experiments using the real-world case of the New Western Land-sea Corridor in China and sensitivity analysis to provide additional insights into policy implications.

The remainder of the paper is organized as follows. Section 2 provides a literature review and discusses the scientific contribution of the article. Section 3 presents the problem description and proposed bi-level formulation. Section 4 offers the model reformulation and solution in detail. Section 5 shows the computation experiment and the analysis. Discussion and managerial implications are provided in Section 6. Finally, Section 7 gives conclusions and directions for future studies.

2. Literature review

Multimodal transportation network design problems are usually studied with bi-level programming models. In the upper-level models typically tackle the design of the networks and decisions such as frequency of transport and capacity of terminals. In the lower-level, the decision is about the mode split and traffic assignment problem (Du et al., 2022; Fan et al., 2022; Wang et al., 2022b). Different methods are proposed to solve these problems, including optimization, simulation, or a combination of both (El Yaagoubi et al., 2022). The interested reader is referred to Archetti et al. (2021) and Crainic et al. (2018) for an overview of different approaches for multimodal transportation problems.

Joint network design and pricing problems have been studied before in combination with bi-level models. In urban transport, Labbé et al. (1998) investigated a pricing problem in a traffic context for a highway network where the highway authority at the upper level seeks to maximize toll revenues by setting the price of arcs of the network. The total cost is minimized from the perspective of users at the lower level. Brotcorne et al. (2000, 2001) extended this work by proposing the multiple commodity network case at the lower level. They also formulated the problem as a bi-level program and solved it using a heuristic algorithm. In a successive study, Brotcorne et al. (2008) presented a more generic mixed-integer bi-level formulation. Both connection decisions and the corresponding rates are decided by the leaders at the upper level, while in the lower layer, users choose the shortest path with the aim of total cost minimization. All these contributions do not explicitly consider time as a service variable or other quality indicators of provided services. More recently, in multimodal urban transport, Loder et al. (2022) proposed a three-dimensional macroscopic fundamental diagram network design problem (3D-MFD-NDP), which optimized the mobility assets and pricing at the upper level while distributing the passenger flows in the lower level.

In the context of multimodal freight transport, to our knowledge, few studies incorporate pricing at the tactical level and consider it with service network design simultaneously. Li and Tayur (2005) investigated multimodal services' pricing and operational planning problems. This paper proposed a formulation with a concave objective function to set prices for two types of services. Ypsilantis and Zuidwijk (2013) limited the scope of the study to a seaport-inland port multimodal transport network and proposed bi-level programming to study the network design and pricing problems simultaneously. At the upper level, the maritime terminal operator tries to maximize profits when considering both economies of scale and service time constraints. In the lower level, the customers try to minimize their system costs by choosing the leader's services, including an all-road alternative. Tawfik and Limbourg (2019) developed a path-based multi-commodity bi-level formulation to maximize profits for a transport operator. For assessing service quality, they propose two approaches: in the first approach, the leader adds a maximum frequency delay constraint in the upper level to guarantee service quality; in the second approach, they integrate the shipper's choice into the cost minimization problem in the lower level. Martin et al. (2021) proposed a novel model to integrate the courier service network design and pricing problems. Their study sets discrete prices for the corresponding guaranteed delivery times to obtain profits when designing the service network. Bilegan et al. (2022) integrated revenue management into the barge multimodal service network design to maximize the carrier's revenue by setting different prices for standard and express delivery demands from several customer categories. They solved the formulation with an industrial solver for real-world instances. Regarding the pricing strategy, our study contributes to the literature in several ways. First, all the studies mentioned above focus on arc-based pricing settings and pricing of a specific set of services. However, an arc-based approach neglects that the end-user price formulated by the LSI is highly correlated with the accurate cost and time calculation of the whole transportation process, leading to difficulties in applying arc-based pricing in practice. A path-based approach has been considered previously but at a single-modal operational level by Crevier et al. (2012) for railway transport. Furthermore, very limited research in freight network optimization implements different pricing for service users with heterogeneous preferences, which is typically incorporated in urban passenger transport research (see for example, Chung and Chiou (2017), Chang et al. (2018) and Zheng and Geroliminis (2020)) with the aim of relieving congestion in urban areas. In the freight transportation domain, Zhang et al. (2015) studied a dynamic pricing strategy for multi-class shippers distinguished by time and cost sensitivity parameters, and used simulation to model the shippers' choices. Bilegan et al. (2022) classified shippers into standard and emergency categories and they set different discrete prices based on the corresponding services. In our study, adding to the above papers, we integrate shippers' heterogeneous preferences (VOT and VOR) as well as the characteristics of the shipment into the pricing strategy within the freight network design problem. This gives more pricing flexibility to the LSI, especially in a multimodal setting.

Secondly, in addition to pricing decisions, the transport time of the multimodal paths is also a significant aspect for the LSI since the service quality perception can be strongly affected by it (Li and Tayur, 2005). Few tactical-level modeling contributions explicitly take into account the time dimension. Some studies consider time requirements by applying minimum frequency constraints or service time required per event (Crainic, 2000). Some works focus on improving service quality. For example, Li et al. (2022b) study a multimodal transportation planning problem trying to minimize the total transportation costs and maximize customers' satisfaction, whose decision is about deciding the path for certain goods and the carriers to perform the transportation. Still, these types of settings are limited in capturing the competition in the market based on the quality of the provided service. Considering competition is necessary in the joint network design and pricing problem, because the pricing and the service operations for multimodal transport require an in-depth understanding of market conditions (Macharis and Bontekoning, 2004). This has been considered in some contributions. For example, Ypsilantis and Zuidwijk (2013) quantified the impact of losing some market share to the competition from truck transportation. Tawfik and Limbourg (2019) also captured the effect of the freight service quality in a competitive setting. However, neither has considered the waiting time of the shipments based on transport frequency decisions, which can directly impact the choice of the shippers for transport services in the lower level.

Finally, research is scant on analyzing the heterogeneous preferences of shippers in the freight service network design problem, which cannot be ignored for the LSIs in making service operation decisions due to the gradual diversification of shippers' needs and preferences. VOT and VOR are used to describe the willingness to pay for reduced transport time and for improved transport time reliability. Li et al. (2022a) proposed a multimodal freight network flow model for China-Europe containerized transportation, which considered the VOT in the logit utility functions. Duan et al. (2019) investigated a service network design problem for freight transport. They identified heterogeneous users through the VOT and VOR to improve the service performance of the network. However, they considered users' heterogeneity from the perspective of the network's minimum total cost, whereas, in our work, we maximize the profit of the LSI. Zhang et al. (2020) used non-negative weight parameters to describe the shipper's heterogeneous preferences. Their results show increased shipper satisfaction and a higher market share for railways, resulting in a more sustainable network. Cheng and Wang (2021) identified the inertia and non-inertial preference of shippers and used the logit model to describe shippers' different behavior in terms of price and time when studying a container liner shipping optimization problem. Bilegan et al. (2022) divided customers into two categories, standard and emergency, based on their due time constraints to maximize revenue for the carrier in a barge transportation network. Zhang et al. (2022) investigated a planning problem in the context of synchromodal transportation. They model heterogeneous preferences of shippers in a set of constraints using multiple attributes and fuzzy theory. All in all, to our knowledge, no study so far has included shippers with heterogeneous preferences in the joint multimodal freight service network and pricing problems at the tactical level of transport planning and considered VOT and VOR.

3. Problem description and modeling

In this section, we define the problem and provide methodological details. We first describe the setting. Next, the mathematical notation and the formulation are introduced.

3.1. Problem setting

We investigate the problem of joint pricing and service network design for an LSI offering multimodal services to a set of shippers with heterogeneous preferences in a competitive transport market to maximize LSI's revenues. The transport network consists of demand nodes, transfer hubs (i.e., inland terminals and seaports), and a destination. The transfer hub refers to a node with the function of consolidating and providing more than one transport service, where containerized cargo can transfer from one mode to another mode. For example, the hub in the inland areas can provide the services for changing from truck to railway, while the hub in the coastal area can provide the services for changing from truck or railway to maritime respectively. Note that transfer hubs can also be the demand nodes. A multimodal network consisting of rail, truck, and maritime services connects these nodes. In addition, we consider a competitor to the LSI, providing a cheaper but slower transport service alternative for shippers. The main decision variables are transport paths, modes, frequencies, and service prices. Due to limited resources and operational restrictions, the frequency (i.e., the number of services in a period) is also limited. The profit is calculated by subtracting all operating costs (i.e., fixed costs, variable costs, unfulfilled demand penalty costs) from the revenue.

We consider a set of shippers with heterogeneous preferences requiring transportation for shipments, each consisting of several standardized container units (TEUs) and with a specific delivery deadline. Shippers may have different service level requirements and price expectations. The service level is related to transport time and transport reliability. Shippers can value them differently, which can be accounted for by variations in VOT or VOR. Besides the service from the competitor of the LSI, shippers can choose to withdraw from the market in case of no suitable transport option. In practice, this usually means that the shippers exit the multimodal transport service market by using direct transport or deferring transport demand to later decision periods. For the sake of simplicity, it is described by the generalized cost bounds in this paper.

The model is constructed based on the following assumptions:

- The shipper is always able to select the competitor as an alternative, independently of its geographical location. The transportation time and price of the competitor depend on the location of the shippers and they indicate the accessibility of the service.
- The competing party cannot react to the LSI's decisions within the considered decisional period, as seen in Ypsilantis and Zuidwijk (2013) and Tawfik and Limbourg (2019). This is a reasonable assumption since slow services such as maritime offerings are not changed regularly within the transport process (Li et al., 2022a).
- We assume that the transport demand from shippers is fixed and known by the LSI in advance. This is a common assumption in the relevant literature as we focus on the case of determining the offline-pricing problem on the tactical level, as seen in Ypsilantis and Zuidwijk (2013), Li et al. (2015) and Tawfik and Limbourg (2019). A common approach to consider uncertainties of demand is the robust optimization method by employing uncertainty sets to capture randomness in the bi-level model. Interested readers are referred to relevant works from Golpîra et al. (2017) and Jiang et al. (2020a).
- The number of containers in the proposed model is considered as a continuous variable. As the flow volumes in the model relate to the number of containers, it would be logical to model them as non-negative integer variables. However, an integer flow variable would cause difficulties in reformulating and computing the model, making its solution quite inefficient. Treating volumes with real numbers creates a need to round numbers to the nearest container. We name this rounding error "fractional freight flows". Its effect on the optimal solution is acceptable as the number of containers to be dealt with in the model is large, and one can assume that carriers always have sufficient excess capacity to absorb an additional container without affecting operations. This is a common assumption made in service network design problems, as seen, for example, in Crevier et al. (2012) and Kurtuluş (2022).

3.2. Mathematical notation

Physical network. We represent the supply side as a graph $G = (N, A)$ where N and A represent the set of nodes and arcs, respectively. Let $M = \{railway, maritime, truck\}$ be the set of transport modes. $A_c \subset \{(i, j, m) : i, j \in N, m \in M\}$ represent the set of transport arcs between a node $i \subset N$ and node $j \in N$ using mode $m \in M$. Note that each arc is seen as a cargo transportation service, so multiple arcs exist between i and j as there may be more than one mode service. For any node n, we denote with $A_{in}(n)$ and $A_{out}(n)$, respectively, the sets of outgoing and incoming arcs.

Multimodal hubs and transfer arcs. $H \subset N$ represents the set of multimodal hubs in the network where the modality change can occur. The modality change refers to the transportation of containers changing from one mode to another mode in the transfer hub after a series of transshipment operations (e.g., unloading and loading), which would cause corresponding transfer costs and transfer times. To model the change of modality, within a node $h \in H$, we define a set of nodes $N_{in}(h)$ for the modalities that arrive at h, and a set $N_{out}(h)$ for the modalities that depart from h. $A(h) := \{(i, j) : i \in N_{in}(h), j \in N_{out}(h)\}$ represent the set of arcs within a node h that connect $N_{in}(h)$ and $N_{out}(h)$. The set of arcs within the hub node h connecting duplicate node sets N_{in} and N_{out} represents the transfer process, meaning that changing from one mode (transport arcs A_c) to another mode (transport arcs A_c).

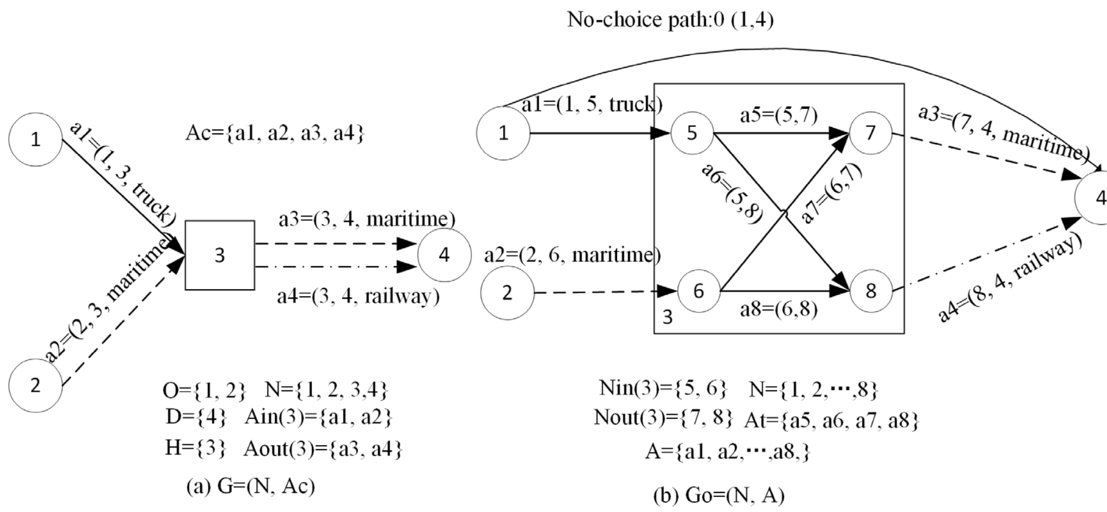

Fig. 1. Multimodal physical and operational networks.

The set of all internal connection arcs is defined as $A_t := \cup_{h\in H} A(h)$. See Wang and Meng (2017) for a similar approach and the graphical representation.

Operational network. From the general network $G := (N, A_c)$, we denote with $G_o := (N, A_c \cup A_t)$ the operational network. Regarding the operational network, following the approach from Wang and Meng (2017), we can more easily and intuitively represent the cargo transfer process from one mode to another by duplicating the hub nodes. Furthermore, by duplicating the hub nodes, we could reduce an extra index, m, which was originally used to represent the mode of parallel arcs between two nodes (e.g., a3 and a4 in Fig. 1a), for modeling and explaining more concisely. An example of the transformation from the physical network (G) to the operational network (G_o) is shown in Fig. 1. In particular, the multimodal hub $h = 3$ in G is expanded into four duplicate nodes (5, 6, 7, and 8) in G_o.

Set of O-D pairs, shipper classes, and shipments. Let $O \subset N$ and $D \subset N$ be the set of origin and destination nodes in the network. S represents the set of shipper classes, and each shipper class has a corresponding VOT_s and VOR_s. K represents the set of shipments. Each shipment $k \in K$ features origin, destination, VOT, VOR, maximum delivery time, and volume in TEU defined by the sextuple $(O_k, D_k, VOT_s, VOR_s, t^k_{max}, q_k)$. Note that we classify shipments based on their inherent characteristics as well as the shipper's preferences. Each shipment k is related to one shipper class s and contains the attribute of VOT_s and VOR_s from the shipper level. For this, we also introduce a parameter ξ^s_k to indicate if shipment k is sent by a shipper from shipper class s. Within K, we distinguish two sets of shipments $K := K_D \cup \overline{K}_D$. In particular, K_D is the set of shipments that can be transported on the competitive path as the transport time can meet the requirement of the maximum delivery time, while shipments in $\overline{K}_D$ have a too short delivery time to be eligible for the competitive path.

Feasible set of paths. Let $L(k) := L^{LSI}_k \cup L^{COMP}_k \cup L^0_k$ be the set of possible paths in the multimodal network for a shipment k, consisting of all the paths for k controlled by the LSI, the path offered by the competitor, and the no-choice path, which represents the choice of exiting the market by the shipper. The LSI's paths are defined by a sequence of arcs belonging to the set $(A_c \cup A_t)$. Parameter δ^l_a equals one if arc $a \in A_c \cup A_t$ is contained in path l, zero otherwise. For the competitor path $L^{COMP}(k)$ for shipment k, the price per TEU, transport time, and reliability are fixed and defined respectively by R_k, B_k and G_k. For the no-purchase path $L^0(k)$, let u^0_k be a constant representing its generalized cost. In practice, a shipper would give up choosing the transport service if the price and the cost of all the available paths are higher than a set level.

Parameters. For each transport/transfer arc $a \in A_c \cup A_t$, we denote c_a as the unit variable cost per TEU; t_a the transport/transfer time; F_a as the fixed cost of operating the transport service once; j_a as the capacity of the transport service at a time; M^a_f as the maximum frequency per period for arc $a \in A_c$. In addition, we define Ψ as the unit penalty cost if the LSI cannot fully use the transport capacity and W as the waiting cost per time unit per TEU caused by the frequency of the transport services.

Decision variables. Binary variable f^k_l for each path $l \in L^{LSI}_k$ of shipment $k \in K$, which takes value 1 if the shipment $k \in K$ is transported on the path $l \in L^{LSI}_k$, and zero otherwise. Continuous variables $z^{LSI}_{k,l}$, z^{COMP}_k and z^o_k denote the number of shipment $k \in K$ transported in the LSI paths, the competitive path, and the no-purchase path, respectively. Note that the no-purchase path is fictitious and represents the exit of the shippers from the system. Variable y_a represents the decision on service frequency on arc $a \in A_c$. Finally, p^k_l is the total user-end price for shipping shipment $k \in K$ on path l.

We summarize the description of the sets, parameters, and decision variables in Table 1.

3.3. Mathematical formulation: bi-level path-based formulation

We present a bi-level model that captures the conflicting interests of the LSI and the shippers. At the upper level, the LSI (seen as the leader) needs to find the optimal pricing, service modes, and frequency decisions to meet the freight demand within the delivery

Table 1
Set, parameters, and variables.

Sets:	
N	Set of nodes indexed by n; $O \subseteq N$, set of origins; $D \subseteq N$, set of destinations; $H \subseteq N$, set of hubs
A	Set of arcs indexed by a; $A_c \subseteq A$, set of transport arcs; $A_t \subseteq A$, set of transfer arcs; $A_c^{truck} \subseteq A_c$, set of highway transport arcs $A_c^{rail} \subseteq A_c$, set of railway transport arcs; $A_c^{maritime} \subseteq A_c$, set of maritime transport arcs
L	Set of paths indexed by l; $L_k^{LSI} \subseteq L$, set of paths controlled by the LSI; $L_k^{COM} \subseteq L$, set of paths controlled by the substitute LSI; $L_k^0 \subseteq L$, set of no-purchase option paths
M	Set of transport mode indexed by m, $M = \{truck, railway, maritime\}$
S	Set of shipper classes indexed by s
K	Set of shipments indexed by k; $K_D \subseteq K$, set of shipments whose delivery time limits are met by the competition paths; $\overline{K}_D \subseteq K$, set of shipments whose delivery time limit cannot be met by the competitive paths
Parameters:	
c_a	Transport cost for delivering unit TEU on arc $a \in A_c$ (USD/TEU)
t_a	Transport/transfer time for delivering unit TEU on arc $a \in A_c \cup A_t$ (h)
e_a	Transport reliability for the service on arc $a \in A_c$, described as average percentage not being delayed (%)
F_a	Fixed cost of operating the transport service once on arc $a \in A_c$ (USD)
j_a	Maximum allowed units of transport service capacity at a time on arc $a \in A_c$ (TEU)
Ψ	Unit penalty cost if the LSI cannot fully use the vehicle capacity (USD)
W	Unit waiting cost caused by the frequency delay (USD)
R_k	Average price of transporting 1 TEU of the shipment $k \in K$ on competing paths
B_k	Average time of transporting 1 TEU of the shipment $k \in K$ on competing paths
G_k	Average reliability of transporting 1 TEU of the shipment $k \in K$ on competing paths
δ_a^l	It equals 1 if arc $a \in A_c \cup A_t$ is on the path $l \in L_l$, and 0 otherwise
ξ_k^s	It equals 1 if shipment $k \in K$ is sent by shipper from shipper class $s \in S$, and 0 otherwise
q_k	Volume of shipment $k \in K$ expressed in TEUs that need to be transported
u_k^o	The cost of no-purchase option for shipment $k \in K$
VOT_s	The value of time of shipper class $s \in S$
VOR_s	The value of reliability of shipper class $s \in S$
t_{max}^k	The maximum delivery time of shipment $k \in K$
M_f^a	Maximum frequency per period for arc $a \in A_c$
T	The given decision period (day)
Decision variables:	
p_l^k	Continuous variable, the user-end price for the whole-process service for shipment $k \in K$ on path $l \in L^{LSI}$
y_a	Continuous variable, service frequency on arc $a \in A_c$, expressed in the number of services per period
f_l^k	Binary variable that equals 1 if shipment $k \in K$ is transported on path $l \in L_k^{LSI}$, and 0 otherwise
$z_{k,l}^{LSI}$	Continuous variable, the amount of shipment $k \in K$ shipped on paths $l \in L_k^{LSI}$
z_k^{COMP}	Continuous variable, the amount of shipment $k \in K$ shipped on paths L_k^{COM}
z_k^o	Continuous variable, the amount of shipment $k \in K$ shipped on paths L_k^0

time limit set by the shippers and, simultaneously, to maximize its profits. Our proposed model aims to help the LSI to differentiate its transport services, serving shippers with different preferences. Such a pricing strategy charges shippers not only based on the characteristics of the shipment (e.g., the maximum delivery time), but also on shipper class membership, which are reflected in the attributes of the shipment in the model. At the lower level, the shippers (seen as followers) aim to minimize their total cost, which consists of transportation fares to be paid to the chosen service provider and the time and reliability costs proportional to VOT and VOR.

We formulate the upper level of the JSNDPP problem as follows:

$$\begin{aligned}\max_{P,y,z} & \sum_{l\in L_k^{LSI}} \sum_{k\in K_D\cup\overline{K}_D} p_l^k z_{k,l}^{LSI} - \sum_{a\in Ac} F_a y_a - \sum_{a\in Ac\cup A_t} \sum_{l\in L_k^{LSI}} \sum_{k\in K_D\cup\overline{K}_D} \delta_a^l c_a z_{k,l}^{LSI} - \\ & - \sum_{a\in A_c\setminus A_c^{truck}} \sum_{l\in L_k^{LSI}} \sum_{k\in K_D\cup\overline{K}_D} \delta_a^l z_{k,l}^{LSI} W(T/2y_a) \\ & - \sum_{k\in K_D\cup\overline{K}_D} \sum_{a\in A_c} \sum_{l\in L_k^{LSI}} \Psi(y_a j_a - \delta_a^l z_{k,l}^{LSI})\end{aligned} \tag{1}$$

Subject to:

$$f_l^k \delta_a^l \Big(\sum_{a\in A_c\setminus A_c^{truck}} T/2y_a + \sum_{a\in A_c\cup A_t} t_a \Big) \le t_{max}^k \qquad \forall k \in K_D \cup \overline{K}_D, l \in L_k^{LSI} \tag{2}$$

$$\sum_{l\in L_k^{LSI}} \sum_{k\in K} z_{k,l}^{LSI} \delta_a^l \le y_a j_a \qquad \forall a \in A_c \tag{3}$$

$$z_{k,l}^{LSI} \le f_l^k M \qquad \forall k \in K_D \cup \overline{K}_D, l \in L_k^{LSI} \tag{4}$$

$$p_l^k \geq 0 \qquad \forall l \in L_k^{LSI}, k \in K_D \cup \overline{K}_D \tag{5}$$

$$f_l^k \in \{0,1\} \qquad \forall k \in K_D \cup \overline{K}_D, l \in L_k^{LSI} \tag{6}$$

$$0 \leq y_a \leq M_f^a \qquad \forall a \in A_c \tag{7}$$

The objective (1) maximizes the LSI's profit, represented as the difference between the revenues generated by serving demands and the sum of four different costs. The first term is the revenue related to the price and the freight volume. This term is non-linear and will be linearized within our solution method. The second term is the fixed operational cost proportional to the frequency, while the third is the variable cost proportional to cargo flows. The fourth term is the cost caused by the average waiting time due to the set frequency y_a. The average waiting time of a shipment depends on the expected delay at the hub based on the frequency of services. Waiting time is commonly represented in the service network design problem as inversely proportional to the frequency and noted as $T/2y_a$ (Ypsilantis and Zuidwijk, 2013; Duan et al., 2019). Finally, we also introduce the penalty cost in the fifth term for the vehicles (e.g., railway) that are not loaded to full capacity because, in long-distance international freight, the capacity may not be fully utilized due to insufficient demand and inefficient transporting planning, etc., which would cause resource waste. A similar penalty cost term is also considered by Zhao et al. (2018) in their study on China railway express location optimization. Constraints (2) ensure that a shipment transported by the LSI reaches the destination before the time limit. The total transport time on path $l \in L_k^{LSI}$ consists of transport time (in-transit and transfer time) and the waiting time. Constraints (3) are the capacity constraints on transport arcs, meaning that the flow quantities on an arc cannot exceed the capacity provided by a certain service, which is related to the operational frequency of the service. With inequalities (4), we connect the $z_{k,l}^{LSI}$ with f_l^k, meaning that there is no cargo flow on path $l \in L_k^{LSI}$ if the LSI does not operate the path. Constraints (5)–(7) define the nature of the variables.

The lower level is formulated as follows:

$$\begin{aligned}\min_{z} \sum_{s\in S}\sum_{k\in K_D\cup\overline{K}_D}\sum_{l\in L_k^{LSI}} z_{k,l}^{LSI}\left(p_l^k + \left(\sum_{a\in A_c\cup A_t} t_a + \sum_{a\in A_c\setminus A_c^{\text{tuck}}} T/2y_a\right)\delta_a^l \xi_k^s VOT_s + \sum_{a\in A_c}\delta_a^l t_a \xi_k^s VOR_s\left(1-e_a\right)\right) \\ + \sum_{s\in S}\sum_{k\in K_D} z_k^{COMP}\left(R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k\left(1-G_k\right)\right) + \sum_{k\in K_D\cup\overline{K}_D} z_k^o u_k^o\end{aligned} \tag{8}$$

Subject to:

$$\sum_{l\in L_k^{LSI}} z_{k,l}^{LSI} + z_k^{COMP} + z_k^o = q_k \qquad \forall k \in K_D \tag{9}$$

$$\sum_{l\in L_k^{LSI}} z_{k,l}^{LSI} + z_k^o = q_k \qquad \forall k \in \overline{K}_D \tag{10}$$

$$z_{k,l}^{LSI} \geq 0 \qquad \forall l \in L_k^{LSI}, k \in K_D \cup \overline{K}_D \tag{11}$$

$$z_k^{COMP} \geq 0 \qquad \forall k \in K_D \tag{12}$$

$$z_k^o \geq 0 \qquad \forall k \in K_D \cup \overline{K}_D \tag{13}$$

The lower-level objective (8) is to minimize the followers' total cost. The cost for flow choosing the services from the LSI makes up the first component of the total cost, while the second part is for choosing the competitor's service and the third for exiting the market. For the first two parts, the cost contains price charging costs, transportation time, and reliability costs. For the LSI's paths, the waiting cost is also included in the form of $1/2y_a$, except for truck-related arcs. Constraints (9)–(10) ensure the demand conservation, showing that the demand q_k for shipment $k \in K_D \cup \overline{K}_D$ are met either by some LSI's paths, by the competitor's path or by the no-purchase path. Finally, constraints (11)–(13) define the nature of the variables.

4. Solution approach

Our bi-level programming is an NP-hard problem. A typical approach to solve bi-level models is to reformulate them as single-level problems using Karush-Kuhn–Tucker (KKT)-based (Yang et al., 2018; Wang et al., 2020; Bhavsar and Verma, 2022) and dual-based reformulation approaches, in which the lower-level is replaced by optimality conditions and added to upper-level constraints (Saharidis and Ierapetritou, 2009).

In this section, we show how to transform the proposed bi-level nonlinear programming to a single-level MILP formulation using a 4-steps methodology. First, we linearize the components related to delays in the formulation. Next, we use the primal–dual optimality conditions to integrate the lower level problem into the upper level. In the third step, we reformulate the nonlinear terms. Finally, we provide tight values for the Big-M constraints.

4.1. Step 1: Frequency discretization and linearization

The proposed model formulation includes the waiting time due to the frequency of services, which is inversely proportional to the frequency variable y_a. To linearize these terms, we use the approach proposed by Martínez et al. (2014). We define a discrete set of frequencies $\Theta = \Theta_{truck} \cup \Theta_{rail} \cup \Theta_{maritime} = \{\theta_1, \theta_2, \ldots \theta_n\}$, where each element θ_i is a non-negative value representing a possible frequency in a transport arc. Next, we also define for each element θ_i, and the time between departures is represented by $1/2\theta_i$. Finally, we introduce a binary variable y_a^i, which takes value 1 if frequency θ_i is set to the transport arc $a \in A_c$. Thus, we replace y_a by the combination of y_a^i, θ_i, j_a, and add the following constraints:

$$\sum_{l \in L_k^{LSI}} \sum_{k \in K_D \cup \overline{K}_D} z_{k,l}^{LSI} \delta_a^l \leq \sum_{i \in \Theta} y_a^i \theta_i j_a \qquad \forall a \in A_c \tag{14}$$

$$\sum_{i \in \Theta} y_a^i = 1 \qquad \forall a \in A_c \tag{15}$$

$$f_l^k \leq \delta_a^l \sum_{a \in A_c \setminus A_c^{truck}} \sum_{i \in \Theta} 2 y_a^i \theta_i \left(t_{\max}^k - \sum_{a \in A_c \cup A_t} t_a \delta_a^l \right) / \mathrm{T} \qquad \forall k \in K_D \cup \overline{K}_D, l \in L_k^{LSI} \tag{16}$$

$$y_a^i = \{0, 1\} \qquad \forall i \in \Theta, a \in A_c \tag{17}$$

In particular, constraints (3) are substituted by constraints (14) by replacing $y_a j_a$ with $y_a^i \theta_i j_a$. Constraints (15) ensure that for each transport arc, there will only be a frequency set on it. Constraints (16) are the linear equivalent of constraints (2) in which the left-hand side expresses that if the shipment will be transported in path l or not, while the right-hand side represents whether the maximum delivery time of shipments is satisfied or not. Eqs. (17) define the nature of the variables.

4.2. Step 2: Primal–dual optimality conditions

Part of the formulation turns into a linear programming problem after implementing Step 1. Next, the bi-level formulation is reduced to single-level programming by replacing the lower-level with its primal–dual optimality conditions.

Let λ_k, $\forall k \in K_D$, and ϖ_k, $\forall k \in \overline{K}_D$ denote the dual variables associated with constraints (9) and constraints (10), respectively, which are not restricted in sign. The dual mathematical formulation of the lower level problem of the JSNDPP is:

$$\max_{\lambda, \varpi} \left(\sum_{k \in K_D} \lambda_k + \sum_{k \in \overline{K}_D} \varpi_k \right) q_k \tag{18}$$

Subject to:

$$\lambda_k \leq \left[p_l^k + \left(\sum_{a \in A_c \cup A_l} t_a + \sum_{a \in A_c \setminus A_c^{truck}} \sum_{i \in \Theta} T y_a^i / (2\theta_i) \right) \delta_a^l \xi_k^s \mathrm{VOT}_s + \sum_{a \in A_c} \delta_a^l t_a \xi_k^s VOR_s (1 - e_a) \right]$$
$$\forall s \in S, k \in K_D, l \in L_k^{LSI} \tag{19}$$

$$\varpi_k \leq \left[p_l^k + \left(\sum_{a \in A_c \cup A_t} t_a + \sum_{a \in A_c \setminus A_c^{truck}} \sum_{i \in \Theta} T y_a^i / (2\theta_i) \right) \delta_a^l \xi_k^s \mathrm{VOT}_s + \sum_{a \in A_c} \delta_a^l t_a \xi_k^s VOR_s (1 - e_a) \right]$$
$$\forall s \in S, k \in \overline{K}_D, l \in L_k^{LSI} \tag{20}$$

$$\lambda_k \leq \left(R_k + \xi_k^s \mathrm{VOT}_s B_k + \xi_k^s VOR_s B_k (1 - G_k) \right) \qquad \forall s \in S, k \in K_D \tag{21}$$

$$\lambda_k \leq u_k^o \qquad \forall k \in K_D \tag{22}$$

$$\varpi_k \leq u_k^o \qquad \forall k \in \overline{K}_D \tag{23}$$

Thus, the optimality conditions of the lower level model include the following components: primal feasibility (constraints (9)–(13)), dual feasibility (constraints(19)–(23)) as well as the following complementarity slackness constraints, derived as seen in Crevier et al. (2012):

$$z_{k,l}^{LSI} \left[p_l^k + \left(\sum_{a \in A_c \cup A_t} t_a + \sum_{a \in A_c} \sum_{i \in \Theta} T y_a^i / (2\theta_i) \right) \delta_a^l \xi_k^s \mathrm{VOT}_s + \sum_{a \in A_c} \delta_a^l t_a \xi_k^s VOR_s (1 - e_a) - \lambda_k \right] = 0$$
$$\forall s \in S, k \in K_D, l \in L_k^{LSI} \tag{24}$$

$$z_{k,l}^{LSI} \left[p_l^k + \left(\sum_{a \in A_c \cup A_t} t_a + \sum_{a \in A_c} \sum_{i \in \Theta} T y_a^i / (2\theta_i) \right) \delta_a^l \xi_k^s \mathrm{VOT}_s + \sum_{a \in A_c} \delta_a^l t_a \xi_k^s VOR_s (1 - e_a) - \varpi_k^w \right] = 0$$
$$\forall s \in S, k \in \overline{K}_D, l \in L_k^{LSI} \tag{25}$$

$$z_k^{COMP} \left[R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k (1 - G_k) - \lambda_k \right] = 0 \qquad \forall s \in S, k \in K_D \tag{26}$$

$$z_k^o (u_k^o - \lambda_k) = 0 \qquad \forall k \in K_D \tag{27}$$

$$z_k^o (u_k^o - \varpi_k) = 0 \qquad \forall k \in \overline{K}_D \tag{28}$$

These three components will be combined with the upper-level formulation to obtain a single-level model. However, the complementary slackness constraints contain new non-linear terms linearized in Step 3.

4.3. Step 3: Linearization of remaining non-linear terms

In this section, we linearize the remaining nonlinear terms in the formulation:

(1)**Linearizing the bilinear term** $p_l^k z_{k,l}^{LSI}$

The bilinear term $p_l^k z_{k,l}^{LSI}$ in the leader's objective function (1) can be linearized using the strong duality theorem. According to the theorem, the value of the objective function of the primal lower-level problem and its dual problem is equal at optimality. Thus, we have:

$$\min_{z} \sum_{s\in S}\sum_{k\in K_D\cup \overline{K}_D}\sum_{l\in L_k^{LSI}} z_{k,l}^{LSI}\left[p_l^k + \left(\sum_{a\in A_c\cup A_t} t_a + \sum_{a\in A_c\setminus A_c^{truck}}\sum_{i\in\Theta} T y_a^i/\left(2\theta_i\right)\right)\delta_a^l \xi_k^s VOT_s + \sum_{a\in A_c}\delta_a^l t_a \xi_k^s VOR_s\left(1-e_a\right)\right]$$
$$+\sum_{s\in S}\sum_{k\in K_D} z_k^{COMP}\left(R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k\left(1-G_k\right)\right) + \sum_{k\in K_D\cup\overline{K}_D} z_k^o u_k^o$$
$$= \max_{\lambda,\varpi}\left(\sum_{k\in K_D}\lambda_k + \sum_{k\in\overline{K}_D}\varpi_k\right) q_k \tag{29}$$

Using this equation, $p_l^k z_{k,l}^{LSI}$ can be rewritten as follows:

$$\sum_{k\in K_D\cup\overline{K}_D}\sum_{l\in L_k^{LSI}} z_{k,l}^{LSI} p_l^k = \left(\sum_{k\in K_D}\lambda_k + \sum_{k\in\overline{K}_D}\varpi_k\right) q_k -$$
$$\sum_{s\in S}\sum_{k\in K_D\cup\overline{K}_D}\sum_{l\in L^{LSI}} z_{k,l}^{LSI}\left[\left(\sum_{a\in A_c\cup A_t} t_a + \sum_{a\in A_c\setminus A_c^{truck}}\sum_{i\in\Theta} T y_a^i/\left(2\theta_i\right)\right)\delta_a^l \xi_k^s VOT_s + \sum_{a\in A_c}\delta_a^l t_a \xi_k^s VOR_s\left(1-e_a\right)\right]$$
$$-\sum_{s\in S}\sum_{k\in K_D} z_k^{COMP}\left(R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k\left(1-G_k\right)\right) - \sum_{k\in K_D\cup\overline{K}_D} z_k^o u_k^o \tag{30}$$

(2) **Linearizing the bilinear term** $z_{k,l}^{LSI} y_a^i$

In (29), the term $z_{k,l}^{LSI} y_a^i$ is linearized by introducing a disjunctive auxiliary variable $\gamma_{i,a}^{k,l}$ and the big-M method. We develop the following linear constraints:

$$\gamma_{i,a}^{k,l} \le z_{k,l}^{LSI} + M_{k,l,i,a}^1\left(1-y_a^i\right) \quad \forall k\in K_D\cup\overline{K}_D, l\in L_k^{LSI}, i\in\Theta, a\in A_c \tag{31}$$
$$\gamma_{i,a}^{k,l} \ge z_{k,l}^{LSI} + M_{k,l,i,a}^1\left(y_a^i-1\right) \quad \forall k\in K_D\cup\overline{K}_D, l\in L_k^{LSI}, i\in\Theta, a\in A_c \tag{32}$$
$$\gamma_{i,a}^{k,l} \le M_{k,l,i,a}^1 y_a^i \quad \forall k\in K_D\cup\overline{K}_D, l\in L_k^{LSI}, i\in\Theta, a\in A_c \tag{33}$$
$$\gamma_{i,a}^{k,l} \ge 0 \quad \forall k\in K_D\cup\overline{K}_D, l\in L_k^{LSI}, i\in\Theta, a\in A_c \tag{34}$$

where $M_{k,l,i,a}^1$ is a large positive number. The roles of constraints (31)–(34) guarantee that the new auxiliary variables $\gamma_{i,a}^{k,l}$ take the value of $z_{k,l}^{LSI}$ if $y_a^i = 1$ and zero if $y_a^i = 0$.

(3) **Linearizing the Complementary Slackness Constraints**

For linearizing Complementary Slackness constraints (constraints (24) to (28)), we introduce a set of binary variables, four variables ($x_{k,l}^1$, $x_{k,l}^2$, $x_{k,l}^3$, $x_{k,l}^4$) for constraints (24) and (25), and six variables (x_k^1, x_k^2, x_k^3, x_k^4, x_k^5, x_k^6) for constraints (26) to (28). Following the complementary slackness definition, all constraints equal zero. We linearize the five constraints (24)–(28) as follows:

$$p_l^k + \left(\sum_{a\in A_c\cup A_t} t_a + \sum_{a\in A_c\setminus A_c^{truck}}\sum_{i\in\Theta} T y_a^i/\left(2\theta_i\right)\right)\delta_a^l \xi_k^s VOT_s + \sum_{a\in A_c}\delta_a^l t_a \xi_k^s VOR_s\left(1-e_a\right) - \lambda_k \le M_{k,l}^1 x_{k,l}^1$$
$$\forall s\in S, k\in K_D, l\in L_k^{LSI} \tag{35}$$
$$z_{k,l}^{LSI} \le M_{k,l}^2 x_{k,l}^2 \quad \forall k\in K_D, l\in L_k^{LSI} \tag{36}$$
$$x_{k,l}^1 + x_{k,l}^2 \le 1 \quad \forall k\in K_D, l\in L_k^{LSI} \tag{37}$$
$$x_{k,l}^1, x_{k,l}^2 \in \{0,1\} \quad \forall k\in K_D, l\in L_k^{LSI} \tag{38}$$
$$p_l^k + \left(\sum_{a\in A_c\cup A_l} t_a + \sum_{a\in A_c\setminus A_c^{truck}}\sum_{i\in\Theta} T y_a^i/\left(2\theta_i\right)\right)\delta_a^l \xi_k^s \mathrm{VOT}_s + \sum_{a\in A_c}\delta_a^l t_a \xi_k^s VOR_s\left(1-e_a\right) - \varpi_k \le M_{k,l}^3 x_{k,l}^3$$
$$\forall s\in S, k\in\overline{K}_D, l\in L_k^{LSI} \tag{39}$$

$$z_{k,l}^{LSI} \le M_{k,l}^4 x_{k,l}^4 \qquad \forall k \in \overline{K}_D, l \in L_k^{LSI} \tag{40}$$

$$x_{k,3}^3 + x_{k,4}^4 \le 1 \qquad \forall k \in \overline{K}_D, l \in L_k^{LSI} \tag{41}$$

$$x_{k,l}^3, x_{k,l}^4 \in \{0,1\} \qquad \forall k \in \overline{K}_D, l \in L_k^{LSI} \tag{42}$$

$$R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k \left(1 - G_k\right) - \lambda_k \le M_k^1 x_k^1 \qquad \forall s \in S, k \in K_D \tag{43}$$

$$z_k^{COMP} \le M_k^2 x_k^2 \qquad \forall k \in K_D \tag{44}$$

$$x_k^1 + x_k^2 \le 1 \qquad \forall k \in K_D \tag{45}$$

$$x_k^1, x_k^2 \in \{0,1\} \qquad \forall k \in K_D \tag{46}$$

$$u_k^o - \lambda_k \le M_k^3 x_k^3 \qquad \forall k \in K_D \tag{47}$$

$$z_k^o \le M_k^4 x_k^4 \qquad \forall k \in K_D \tag{48}$$

$$x_k^3 + x_k^4 \le 1 \qquad \forall k \in K_D \tag{49}$$

$$x_k^3, x_k^4 \in \{0,1\} \quad \forall k \in K_D \tag{50}$$

$$u_k^o - \varpi_k \le M_k^5 x_k^5 \quad \forall k \in \overline{K}_D \tag{51}$$

$$z_k^o \le M_k^6 x_k^6 \quad \forall k \in \overline{K}_D \tag{52}$$

$$x_k^5 + x_k^6 \le 1 \quad \forall k \in \overline{K}_D \tag{53}$$

$$x_k^5, x_k^6 \in \{0,1\} \quad \forall k \in \overline{K}_D \tag{54}$$

where $M_{k,l}^1$, $M_{k,l}^2$, $M_{k,l}^3$, $M_{k,l}^4$, M_k^1, M_k^2, M_k^3, M_k^4, M_k^5, M_k^6 are a large positive number.

Finally, the proposed bi-level programming model is reformulated as a MILP model as follows:

$$\begin{aligned}
\max_{p,y,f,z,\lambda,\varpi} = & \left(\sum_{k\in K_D} \lambda_k + \sum_{k\in \overline{K}_D} \varpi_k \right) q_k - \sum_{s\in S} \sum_{k\in K_D \cup \overline{K}_D} \sum_{l\in L_k^{LSI}} z_{k,l}^{LSI} \sum_{a\in A_c \cup A_t} t_a \delta_a^l \xi_k^s VOT_s - \\
& \sum_{s\in S} \sum_{k\in K_D \cup \overline{K}_D} \sum_{l\in L_k^{LSI}} \sum_{a\in A_c \setminus A_c^{truck}} \sum_{i\in\Theta} \delta_a^l T \gamma_{i,a}^{k,l} / \left(2\theta_i\right) \xi_k^s VOT_s - \sum_{s\in S} \sum_{k\in K_D \cup \overline{K}_D} \sum_{l\in L_k^{LSI}} z_{k,l}^{LSI} \sum_{a\in A_c} \delta_a^l t_a \xi_k^s VOR_s \left(1 - e_a\right) \\
& - \sum_{s\in S} \sum_{k\in K_D} z_k^{COMP} \left(R_k \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k \left(1 - G_k\right)\right) - \sum_{k\in K_D \cup \overline{K}_D} z_k^o u_k^o - \sum_{a\in Ac} \sum_{i\in\Theta} F_a y_a^i \theta_i - \\
& \sum_{a\in Ac \cup A_t \setminus A_c^{rail}} \sum_{l\in L_k^{LSI}} \sum_{k\in K_D \cup \overline{K}_D} \delta_a^l c_a z_{k,l}^{LSI} - \sum_{a\in A_c^{rail}} \sum_{l\in L_k^{LSI}} \sum_{k\in K_D \cup \overline{K}_D} \delta_a^l c_a z_{k,l}^{LSI} - \\
& \sum_{a\in A_c \setminus A_c^{truck}} \sum_{l\in L_k^{LSI}} \sum_{k\in K_D \cup \overline{K}_D} \sum_{fr\in\Theta} \delta_a^l \gamma_{i,a}^{k,l} WT / \left(2\theta_i\right) - \sum_{a\in A_c} \Psi \left(\sum_{i\in\Theta} y_a^i \theta_i j_a - \sum_{k\in K_D \cup \overline{K}_D} \sum_{l\in L^{LSI}} \delta_a^l z_{k,l}^{LSI} \right)
\end{aligned} \tag{55}$$

Subject to: (4)–(6), (9)–(17), (19)–(23), (31)–(54)

4.4. Step 4: Tight values for the Big-M constants

Making the M values as small as possible helps improve the branch-and-cut performance. In particular, the flow variables $z_{k,l}^{LSI}$, z_k^{COMP} and z_k^o cannot be larger than the corresponding shipment's demand q_k. Hence, we replace the $M_{k,l,i,a}^1$, $M_{k,l}^2$, $M_{k,l}^4$, M_k^2, M_k^4, M_k^6 in constraints (31)–(33), (36), (40), (44), (48) and (52) with shipment's demand q_k.

To find a good bound for $M_{k,l}^1$, $M_{k,l}^3$, M_k^1, M_k^3 and M_k^5, we need to analyze the dual variables λ_k and ϖ_k appearing in the linearized complementary slackness constraints (35), (39), (43), (47) and (51). The right-hand sides of constraints (19) and (20) are non-negative, since $p_l^k \ge 0$. Similarly, we consider non-negative competition's cost $(R_k + VOT_s B_k + VOR_s B_k \left(1 - G_k\right))$ and non-negative no-choice path cost u_k^o, making the right-hand sides of constraints (21)–(23) also non-negative. Consequently, the non-negativity of the optimal dual solution $\lambda_k^* \ge 0$ and $\varpi_k^* \ge 0$ for each shipment $k \in K$ can be inferred. Based on this inference, for $M_{k,l}^1$ and $M_{k,l}^3$ in constraints (35) and (39), respectively, we observe that the leader can raise the additive prices of LSI's controlled paths when the competitive path does not meet the maximum time requirement of shipment $k \in \overline{K}_D$, but the no-choice path total cost u_o^k provides the upper bound as shippers will choose the no-purchase path if the total cost of leader's controlled paths reaches u_k^o. Thus, we replace $M_{k,l}^1$ and $M_{k,l}^3$ with u_k^o. For M_k^1, M_k^3 and M_k^5, taking constraints (43) as an example, $(R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k \left(1 - G_k\right))$ is assigned to the value of corresponding big M since it bounds the difference $[(R_k + \xi_k^s VOT_s B_k + \xi_k^s VOR_s B_k \left(1 - G_k\right))$-$\lambda_k]$. Similar analysis can be provided to $(u_k^o - \lambda_k)$ and $(u_k^o - \varpi_k)$ in constraints (47) and (51), and we can replace M_k^3 and M_k^5 with u_k^o.

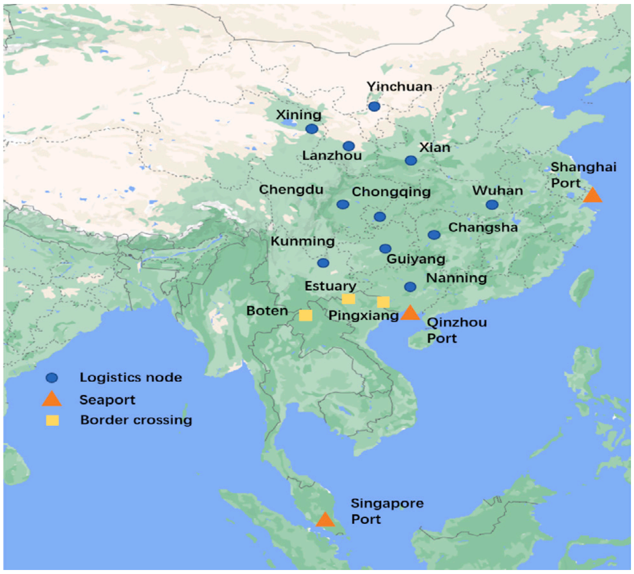

Fig. 2. Physical network under study.

5. Proof of concept for the proposed modeling approach

5.1. Case study

In this section, we demonstrate the model's applicability to the real-world case of the New Western Land-Sea Corridor in China. Recently, China released a plan to build this corridor, which is intended to provide faster transportation services between China's western inland areas and the surrounding ASEAN region. This complements the popular inland shipping connection from Chongqing to Shanghai port, followed by transportation over the sea to the south, also known as the Golden Waterway of the Yangtze River; see Fig. 2. Even though the corridor has a time advantage, more competitive pricing and suitable combinations of transport services are necessary to attract more shippers.

The logistic nodes are selected in accordance with the logistics hub layout in the Overall Plan for the New Western Land-sea Corridor in China (National Development and Reform Commission, 2019). Because our model decision-making is on the tactical level, the logistic node selection and demand aggregation are focused on the main industrial centers per province. Thus, we consider these cities as centroid, as shown in Fig. 2, which are the origins of the flows. The port of Singapore is the common final destination. The LSI decides the price and designs the service network against the main competing corridor, the Yangtze River Golden Waterway corridor.

5.2. Data input and experimental setting

In this case study, we model the real network, where links representing different modes between nodes already exist. For the information and data on the links in detail, we refer to Wang and Meng (2017), Jiang et al. (2020b) and Zhu et al. (2023), and also public sources such as *China Railway 95306 Website* (http://www.95306.cn/). The operational multimodal transport network comprises three transport modes, 111 arcs (including 53 transport arcs and 58 transfer arcs), and 62 nodes (including the duplicate nodes), as shown in Fig. 3. Note that all costs used in the experiments were considered using the Chinese currency RMB, based on the available data. However, in this paper, we display the values and the results in USD for better understanding. At the time of research, the exchange rate from USD to RMB was 1:7.

To analyze the effect of heterogeneous preference considerations on LSI decision-making, we consider two kinds of shippers in the network who have different valuations of time and reliability. In particular, Class 1 is more likely to be attracted to low prices with lower VOT and VOR, while shippers in Class 2 are highly sensitive to time and reliability attributes. Classes 1 and 2 are further divided into two shipment types based on the maximum delivery time. The values of VOT and VOR of the shipper classes originate from Duan et al. (2019). The information on freight shipments is shown in Table 2.

For the shipments that, due to time constraints, can only be transported by the LSI, we need to define a value for the no-purchase option. Although this value can be estimated via Stated Preference (SP) surveys (Khakdaman et al., 2020; Ren et al., 2022), this investigation is out of the scope of this paper. Here, we set the total cost u_o^k of the no-purchase option for each shipment $k \in K$ as a 10% increase on its corresponding cost in choosing the competing path. The influence of different increase levels on the optimal solution is analyzed in a sensitivity analysis further below.

Table 2
Parameters for freight shipments.

Shipper class	Shipment	VOT (USD/TEU·h)	VOR (USD/TEU·h)	Maximum delivery time (days)
class 1 ($s1$)	$k1$	2.3	2.8	31
	$k2$	2.3	2.8	35
class 2 ($s1$)	$k3$	5.7	15.2	10
	$k4$	5.7	15.2	18

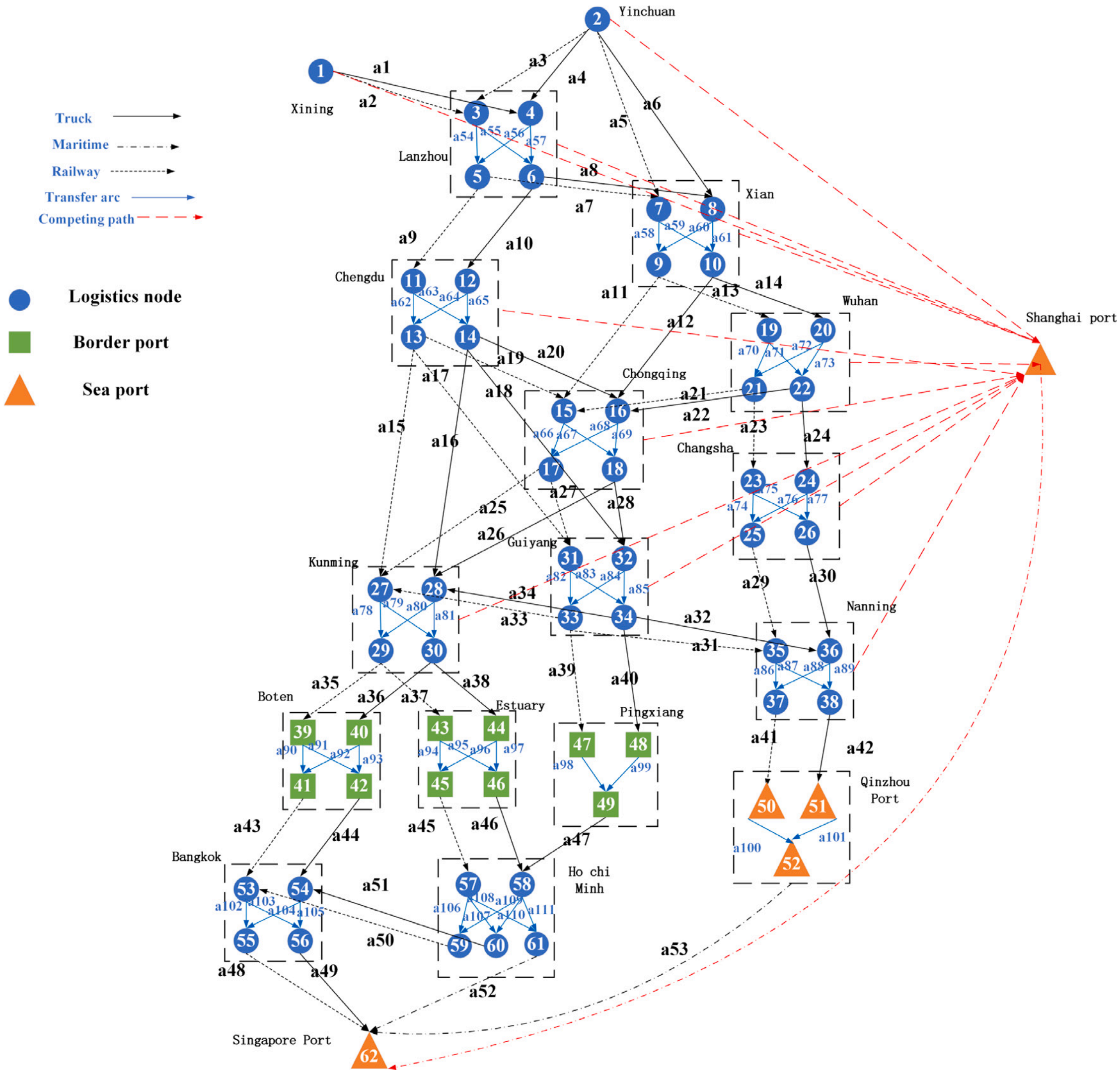

Fig. 3. Operational transportation network.

For this real-world case, we configure a set of possible values of frequencies (per month) to reflect the limited capacity and different frequency setting situations for each transport mode: $\Theta_{maritime}$ = (0, 1, 2, 3, 4, 5, 6, 7, 8, 9); $\Theta_{railway}$ = (0, 10, 20, 30, 40, 50, 60, 70, 80, 90); Θ_{truck} = (0, 100, 200, 300, 400, 500, 600, 700, 800, 900). By setting the finite sets of discrete frequencies within each decision period, we consider that there will be a maximum number of frequencies of different services in the upper level, which can be seen as limited resources and operational restrictions. From a preliminary experiment, altering the link travel time and link travel cost does not generate significant changes in the model behavior. Hence, the values proposed in Table 3 are used for the experiments. The rest of the parameters are set as follows. For the competing path, the parameters for each OD pair are fixed. Taking one OD as an example, the total transport cost (river-sea transport route) from Chongqing to Singapore is 1143 USD/TEU, the total transport time is 31 days, and the reliability is 70%. The penalty and waiting time costs for the new corridor are set to 142.86 USD/TEU and 0.71 USD/(TEU.h), respectively.

Table 3
Main parameters of the modes of transportation.
Data sources: Lam and Gu (2016), Qu et al. (2016), Zhao et al. (2018) and Wei and Dong (2019).

Transport mode		Truck	Rail	Maritime
Variable transport cost (USD/km)		1.86	1.39	0.28
Average speed (km/h)		90	60	30
Capacity (TEU)		2	45	3000
Fixed cost of operating service per time (USD)		714	2857	3643
Transfer cost/time(USD/TEU)/(Days)	Truck	0/0	17.14/0.3	67.86/0.5
	Rail	17.14/0.3	0/0	70.71/0.5
	Maritime	67.86/0.5	70.71/0.5	0/0

Table 4
Description of the ODs in the network.

Instance setting	No. of OD pairs	Demand origins	No. of shipments	No. of paths
1	3	Changsha, Nanning, Guiyang	12	137
2	4	Changsha, Nanning, Guiyang, Chongqing	16	516
3	5	Changsha, Nanning, Guiyang, Chongqing, Kunming	20	574
4	6	Changsha, Nanning, Guiyang, Chongqing, Kunming, Wuhan	24	1340
5	7	Changsha, Nanning, Guiyang, Chongqing, Kunming, Wuhan, Chengdu	28	2477

Table 5
Results for the five sets of instances. Best integer solution is related to the value of the profit for the best feasible solution found.

Instance	Shipment	Unified pricing				Shipment-based pricing				Profit difference
set	proportion	Best integer solution (a)	Best bound	Gap %	Times (s)	Best integer solution (b)	Best bound	Gap %	Times (s)	% [(b-a)/a]
1	5:5:1:1	8.23×10^6	–	0	57.1	1.11×10^7	–	0	9.81	34.87%
1	3:3:3:3	1.20×10^7	–	0	49.3	1.70×10^7	–	0	11.4	41.70%
1	1:1:5:5	2.14×10^7	–	0	10.7	2.29×10^7	–	0	8.86	7.00%
2	5:5:1:1	8.83×10^6	–	0	667	1.26×10^7	–	0	47.9	45.26%
2	3:3:3:3	1.39×10^7	–	0	1214	2.06×10^7	–	0	44.2	48.20%
2	1:1:5:5	2.70×10^7	–	0	78.2	2.86×10^7	–	0	56.1	5.93%
3	5:5:1:1	9.96×10^6	–	0	7616	1.46×10^7	–	0	382	46.58%
3	3:3:3:3	1.69×10^7	–	0	2188	2.46×10^7	–	0	383	45.56%
3	1:1:5:5	3.01×10^7	–	0	896	3.45×10^7	–	0	458	14.62%
4	5:5:1:1	1.02×10^7	–	0	12 358	1.53×10^7	–	0	1120	49.95%
4	3:3:3:3	1.79×10^7	–	0	10 261	2.67×10^7	–	0	1664	49.16%
4	1:1:5:5	3.19×10^7	–	0	2894	3.81×10^7	–	0	1314	19.43%
5	5:5:1:1	1.16×10^7	1.78×10^7	53.3	335	1.77×10^7	1.91×10^7	7.70	522	×
5	3:3:3:3	2.40×10^7	3.00×10^7	25.3	633	3.10×10^7	3.37×10^7	8.85	315	×
5	1:1:5:5	4.23×10^7	4.59×10^7	8.38	647	4.37×10^7	4.74×10^7	8.30	283	×

The experimental setting is described as follows. First, in Section 5.3, we quantify the benefits of applying heterogeneous pricing to the shippers. Then, in Section 5.4, we conduct a sensitivity analysis on three important parameters: the waiting time cost, the penalty cost, and the increased level of u_o^k.

The MILP model was solved using the IBM ILOG CPLEX 12.6 library as a branch-and-bound (B&B) solver with default parameterization, and the code was implemented in Java. The computational time limit was set to 4 h with an emphasis on balancing optimality and feasibility. We use a computer with an Intel Core i7-11370H 3.3 GHz processor and 16 GB of RAM.

5.3. Shipment-based pricing vs. unified path-based pricing strategy

We analyze the effects of two different pricing strategies. In the first, the LSI sets a unified path-based price regardless of the shippers' heterogeneity, which means we remove the k superscript in (1) and (8) in the model. In the second, the LSI sets the shipment-based pricing, which is a user-end service price that varies per path, and per kind of shipment. Even though the pricing is shipment-based, we note that each shipment also takes attributes (VOT_s and VOR_s) from the shipper class that is sending it. To further explore how the shippers' class composition affects LSI's decisions, we set the ratios of the four shipment types $k1 : k2 : k3 : k4$ to 5:5:1:1, 3:3:3:3, and 1:1:5:5 and for each origin the same total volume of shipment to 1200 TEUs. The current O/D pairs were chosen as the key nodes that covered the main targeted areas in China of the New Western Land-Sea Corridor (National Development and Reform Commission, 2019) and were shown to provide several new managerial insights. We consider five instances differing in the number of origins, from three to seven. The details of the five instances used in the expanded network are presented in Table 4.

About the computational effort required, as shown in Table 5, optimal solutions are obtained for the first four instances for the two pricing strategies with the different shipment proportions within 4 h. The solver also finds a feasible solution for the fifth

Table 6
Results of service operation for the instance 1.

Service operation	Unified pricing			Shipment-based pricing		
	5:5:1:1	3:3:3:3	1:1:5:5	5:5:1:1	3:3:3:3	1:1:5:5
Service arc(mode): frequency	a29(railway): 20 a31(railway): 10 a32(truck): 100 a41(railway): 40 a53(maritime): 5	a29(railway): 10 a31(railway): 10 a41(railway): 20 a53(maritime): 5	a29(railway): 10 a31(railway): 10 a41(railway): 30 a53(maritime): 7	a29(railway): 20 a31(railway): 10 a32(truck): 100 a41(railway): 40 a53(maritime): 6	a29(railway): 20 a31(railway): 20 a41(railway): 40 a53(maritime): 6	a29(railway): 20 a31(railway): 20 a41(railway): 40 a53(maritime): 7
Operated path (pricing): shipment transportation (volume)	a29-a41-a53(4241): O1-S1(500) O1-S2 (500) O1-S3(100) O1-S4(100) a41-a53(4508): O2-S1(500) O2-S2(500) O2-S3(100) O2-S4(100) a31-a41-a53(3835): O3-S1(500) O3-S2(500) a32-a41-a53(4046): O3-S3(100) O3-S4(100)	Competing paths: O1-S1(300) O1-S2 (300) O2-S1(300) O2-S2(300) O3-S1(300) O3-S2(300) O4-S1(300) O4-S2(300) a29-a41-a53(8830): O1-S3(300) O1-S4(300) a41-a53(9726): O2-S3(300) O2-S4(300) a31-a41-a53(7873): O3-S3(300) O3-S4(300)	Competing paths: O1-S1(100) O1-S2 (100) O2-S1(100) O2-S2(100) O3-S1(100) O3-S2(100) O4-S1(100) O4-S2(100) a29-a41-a53(8981): O1-S3(500) O1-S4(500) a41-a53(9877): O2-S3(500) O2-S4(500) a31-a41-a53(8410): O3-S3(500) O3-S4(500)	a29-a41-a53(4269): O1-S1(500) O1-S2 (500) a29-a41-a53(9052): O1-S3(100) O1-S4(100) a41-a53(4535): O2-S1(500) O2-S2(500) a41-a53(9846): O2-S3(100) O2-S4(100) a31-a41-a53(3862): O3-S1(500) O3-S2(500) a32-a41-a53(8590): O3-S3(100) O3-S4(100)	a29-a41-a53(4269): O1-S1(300) O1-S2 (300) a29-a41-a53(9052): O1-S3(300) O1-S4(300) a41-a53(4535): O2-S1(300) O2-S2(300) a41-a53(9846): O2-S3(300) O2-S4(300) a31-a41-a53(3904): O3-S1(300) O3-S2(300) a31-a41-a53(8481): O3-S3(300) O3-S4(300)	a29-a41-a53(4289): O1-S1(100) O1-S2 (100) a29-a41-a53(9101): O1-S3(500) O1-S4(500) a41-a53(4555): O2-S1(100) O2-S2(100) a41-a53(9894): O2-S3(500) O2-S4(500) a31-a41-a53(3924): O3-S1(100) O3-S2(100) a31-a41-a53(8529): O3-S3(500) O3-S4(500)

instance with an acceptable gap. As expected, the computational effort is quite sensitive to the number of OD pairs and also related to the shipment proportion. In general, even in a complex multimodal transport logistics system, the computational test shows that our proposed model is suitable for practical purposes.

The last column of Table 5 shows that the profit of the LSI can improve substantially (up to 49.95%) when implementing the shipment-based pricing. Higher profit difference increases are achieved in the first four instances with the proportion of 5:5:1:1 and 3:3:3:3 compared to 1:1:5:5. For the sake of simplicity, we show the results of service operation for instance 1 in Table 6 to study the trend of profit under two pricing strategies obtained in Table 5. For clarity, we name each origin in O, e.g., O1-S1 means shipment one from origin number one, as shown in the table. The second row in the first column illustrates the frequency of operated services (represented by arc and mode) per month. The third row in the first column illustrates the volume of various shipments (in TEUs) on the path being operated and the pricing (in USD) for that path. From the pricing and transportation of the shipment in the second column, when the proportion is 5:5:1:1, we can see the LSI serves all the shipments under the two pricing ways and charges higher prices to high-value shipment types after implementing the shipment-based pricing to improve profits. For the proportion of 3:3:3:3 and 1:1:5:5, after implementing shipment-based pricing, the LSI captures back the shipments served by the competing paths and makes the price based on the shipper types to improve profits. Moreover, the reason for the higher profit difference increases achieved in the first two proportions compared to the last is that the quantity differences in high-value shipments served by the LSI are higher in the first two proportions.

5.4. Sensitivity analysis

We perform a sensitivity analysis on three critical parameters on instance 3 containing the main operational areas: the level of frequency discretization, the waiting time cost, the penalty cost, and the increased level of u_o^k. This section analyzes the obtained profit and network operations under different scenarios and provides further managerial suggestions.

5.4.1. The effect of the level of frequency discretization of different modes

In this experiment, we compare results obtained from different sets of possible frequencies for instance 3 with shipment types ratios of 1:1:5:5 to investigate how different levels of discretization impact the accuracy of the solution results and the required computing time. Table 7 shows the frequency setting and corresponding optimal objective and the computing time. The third row corresponds to the results already reported in Section 5.3 of the case study. Keeping other parameters the same, we add a frequency setting with a lower discretization level shown in the second row. Frequency settings start at 0 and increase the intervals of frequency sets for maritime, railway, and truck to 2, 20, and 200, respectively, to get a set of 5 frequency options for each mode of transport. Analogously, a frequency setting with a higher discretization level is also set in the fourth row, where the intervals of frequency sets for maritime, railway, and truck are decreased to 0.5, 5, and 50, respectively, to get a set of 19 frequency options.

We can observe that, in the experiment with the frequency set with a lower discretization level, the objective has a 0.77% reduction to 34 242 888 compared to the previous setting, while the computing time decreased to 51.6 s. When increasing the discretization level of the frequency set shown in the fourth row in the table, the objective gets a 0.69% increase to 34 745 987, and the computing also increases to 2121 s at the same time. This experiment shows that higher levels of frequency discretization can increase LSI's profitability to a very small extent and but at the cost of a much larger computation time.

Table 7
Sensitivity analysis of the set of possible frequencies of different modes.

Frequency set	Obj. (USD)	Time (s)
$\Theta_{maritime}$ = (0, 2, 4, 6, 8) $\Theta_{railway}$ = (0, 20, 40, 60, 80) Θ_{truck} = (0, 200, 400, 600, 800)	34 242 888	51.6
$\Theta_{maritime}$ = (0, 1, 2, 3, 4, 5, 6, 7, 8, 9) $\Theta_{railway}$ = (0, 10, 20, 30, 40, 50, 60, 70, 80, 90) Θ_{truck} = (0, 200, 400, 600, 800)	34 506 109	458
$\Theta_{maritime}$ = (0, 0.5, 1, 1.5, ..., 9) $\Theta_{railway}$ = (0, 5, 10, 15, ..., 90) Θ_{truck} = (0, 50, 100, 150, ..., 900)	34 745 987	2121

Table 8
Sensitivity of the waiting time cost W with different proportions under two pricing strategies.

Unified pricing								
Shipment proportion	The value of W (USD/TEU.h)	Profit (USD)	Cost components (USD)			Frequency of operated services		
			Transportation cost	Waiting cost	Penalty cost	Truck	Railway	Maritime
5:5:1:1	0.18	10 647 949	10 561 133	103 500	600 000	500	90	8
5:5:1:1	0.36	10 149 186	10 344 355	196 714	828 571	300	110	8
5:5:1:1	0.71	9 952 598	10 238 847	387 000	885 714	100	120	8
5:5:1:1	1.43	9 597 864	10 242 490	708 857	1 028 571	100	120	9
5:5:1:1	2.86	8 956 399	10 249 775	1 221 796	1 314 286	100	120	11
3:3:3:3	0.18	17 069 568	6 445 603	63 000	1 285 714	0	90	9
3:3:3:3	0.36	17 006 568	6 445 603	126 000	1 285 714	0	90	9
3:3:3:3	0.71	16 880 568	6 445 603	252 000	1 285 714	0	90	9
3:3:3:3	1.43	16 628 568	6 445 603	504 000	1 285 714	0	90	9
3:3:3:3	2.86	16 162 406	7 358 803	805 224	1 142 857	0	100	7
1:1:5:5	0.18	30 368 365	10 564 600	86 786	1 000 000	0	100	12
1:1:5:5	0.36	30 281 580	10 564 600	173 571	1 000 000	0	100	12
1:1:5:5	0.71	3 010 800	10 564 600	347 143	1 000 000	0	100	12
1:1:5:5	1.43	29 760 865	10 564 600	694 286	1 000 000	0	100	12
1:1:5:5	2.86	29 098 208	10 571 886	1 280 000	1 285 714	0	100	14
Shipment-based pricing								
Shipment proportion	The value of W (USD/TEU.h)	Profit (USD)	Cost components (USD)			Frequency of operated services		
			Transportation cost	Waiting cost	Penalty cost	Truck	Railway	Maritime
5:5:1:1	0.18	14 943 947	12 791 563	103 886	1 000 000	0	160	9
5:5:1:1	0.36	14 840 062	12 791 563	207 771	1 000 000	0	160	9
5:5:1:1	0.71	14 633 513	12 795 206	386 155	1 142 857	0	160	10
5:5:1:1	1.43	14 255 829	12 798 849	720 882	1 285 714	0	160	11
5:5:1:1	2.86	13 565 362	12 802 491	1 353 600	1 428 571	0	160	12
3:3:3:3	0.18	24 814 696	12 798 849	90 110	1 285 714	0	160	11
3:3:3:3	0.36	24 724 586	12 798 849	180 220	1 285 714	0	160	11
3:3:3:3	0.71	24 544 366	12 798 849	360 441	1 285 714	0	160	11
3:3:3:3	1.43	24 204 935	12 802 491	676 800	1 428 571	0	160	12
3:3:3:3	2.86	23 547 821	12 809 777	1 223 314	1 714 286	0	160	14
1:1:5:5	0.18	34 759 909	12 802 491	84 600	1 428 571	0	160	12
1:1:5:5	0.36	34 675 309	12 802 491	169 200	1 428 571	0	160	12
1:1:5:5	0.71	34 506 109	12 802 491	338 400	1 428 571	0	160	12
1:1:5:5	1.43	34 178 466	12 806 134	642 514	1 571 429	0	160	13
1:1:5:5	2.86	33 561 840	12 809 777	1 223 314	1 714 286	0	160	14

5.4.2. The effect of waiting time cost W

We study the effect of waiting time cost W by considering the base value ($W = 0.71$) multiplied by $[1/4, 1/2, 2, 4]$. We display the cost components (transportation cost, waiting time cost, and penalty cost) and the service operation (the total frequency of different modes operated in the network) in Table 8.

The first part of Table 8 shows the sensitivity analysis results under different shipment proportions when implementing unified pricing. As expected, a decrease in profit and an increase in the total waiting time cost can be observed with the increase in the value of W. In the proportion of 5:5:1:1, trucks are always used to serve shippers. The LSI operates more railways and maritime transports, and decreases the truck services with the increase of W, which leads that the transportation cost decreased slightly and then increases slowly after the W is up to 0.71. Differently, the LSI only uses railways and maritime transports in the proportion of 3:3:3:3 and 1:1:5:5, leading to the increasing trend of the transportation cost with the increase of waiting time cost. Similar changes also happen for the penalty cost when the W increases.

Table 9
Sensitivity of the penalty cost Ψ with different proportions under two pricing strategies.

Unified pricing								
Shipment proportion	The value of Ψ (USD/TEU)	Profit (USD)	Cost components (USD)			Frequency of operated services		
			Transportation cost	Waiting cost	Penalty cost	Truck	Railway	Maritime
5:5:1:1	35.71	11 001 198	10 151 113	253 857	500 000	0	130	15
5:5:1:1	71.43	10 556 469	10 140 184	293 143	785 714	0	130	12
5:5:1:1	142.86	9 952 598	10 238 847	387 000	885 714	100	120	8
5:5:1:1	285.71	9 524 155	10 713 064	524 571	400 000	600	80	6
5:5:1:1	571.43	9 197 093	10 926 436	527 143	571 429	900	70	6
3:3:3:3	35.71	18 146 311	6 467 460	192 000	535 714	0	90	15
3:3:3:3	71.43	17 645 539	6 460 174	204 857	928 571	0	90	13
3:3:3:3	142.86	16 880 568	6 445 603	252 000	1 285 714	0	90	9
3:3:3:3	285.71	16 033 666	7 752 800	262 286	971 429	500	70	4
3:3:3:3	571.43	15 176 509	7 749 157	313 714	1 371 429	500	70	3
1:1:5:5	35.71	31 269 108	10 749 957	240 714	607 143	0	150	17
1:1:5:5	71.43	30 744 165	10 709 243	260 000	1 000 000	0	140	15
1:1:5:5	142.86	30 108 008	10 564 600	347 143	1 000 000	0	100	12
1:1:5:5	285.71	29 400 080	10 553 671	411 429	1 142 857	0	100	9
1:1:5:5	571.43	29 155 364	12 047 314	437 143	0	0	110	4
Shipment-based pricing								
Shipment proportion	The value of Ψ (USD/TEU)	Profit (USD)	Cost components (USD)			Frequency of operated services		
			Transportation cost	Waiting cost	Penalty cost	Truck	Railway	Maritime
5:5:1:1	35.71	15 749 347	12 813 420	295 543	464 286	0	160	15
5:5:1:1	71.43	15 308 430	12 809 777	305 829	857 143	0	160	14
5:5:1:1	142.86	14 633 513	12 795 206	386 155	1 142 857	0	160	10
5:5:1:1	285.71	14 088 409	13 379 014	553 371	400 000	400	110	7
5:5:1:1	571.43	13 753 818	13 592 386	555 429	571 429	900	100	7
3:3:3:3	35.71	25 788 682	12 817 063	288 196	500 000	0	160	16
3:3:3:3	71.43	25 322 450	12 809 777	305 829	857 143	0	160	14
3:3:3:3	142.86	24 544 366	12 798 849	360 441	1 285 714	0	160	11
3:3:3:3	285.71	23 720 957	13 382 657	501 943	685 714	600	110	8
3:3:3:3	571.43	23 326 585	13 592 386	555 429	571 428	900	100	7
1:1:5:5	35.71	35 836 123	12 820 706	282 686	535 714	0	160	17
1:1:5:5	71.43	35 345 466	12 813 420	295 543	928 571	0	160	15
1:1:5:5	142.86	34 506 109	12 802 491	338 400	1 428 571	0	160	12
1:1:5:5	285.71	33 447 507	13 227 083	450 514	1 200 000	500	120	9
1:1:5:5	571.43	32 988 771	14 277 443	426 857	114 286	700	110	5

A minor upward trend in all cost components and a downward trend in profits can be observed under different proportions in the second part of Table 8, which shows the results of the implementation of shipment-based pricing. This is because the service operation and shipment allocation are relatively stable with the implementation of shipment-based pricing, which gives more flexibility in pricing.

5.4.3. The effect of penalty cost Ψ

We study the effect of penalty cost Ψ, which is a penalty cost for the LSI that does not make full use of the capacity, by considering the base value (Ψ = 142.86) multiplied by [1/4, 1/2, 2, 4]. The cost component and the service operation (the total frequency of different modes operated in the network) are shown in Table 9.

The first part of Table 9 shows the sensitivity analysis results under different shipment proportions when implementing unified path-based pricing. The profit decreases slightly, and the waiting time cost increase slightly simultaneously with the increase in the value of Ψ. The change of service operation can explain the non-monotonic variation of the transportation and penalty costs. For example, when the proportion is 5:5:1:1, the transportation cost decreases with the increase in the Ψ up to 71.43 because the LSI operates lower maritime frequency to reduce the penalty cost. Then the tipping point shows up after the Ψ value of 71.43 because the LSI starts to operate truck services and decreases the railway services significantly to reduce the not fully loaded degree, but leads to higher operational costs at the same time. It is noted that a noticeable difference in the service operation is shown with the proportion of 1:1:5:5, in which the LSI operates high frequencies of railway and maritime instead of trucks with the increase in the Ψ. This is because the targeted shipper (high-value shippers) of the LSI takes up a large part of the shipper group, which makes it possible to balance penalty costs with operating costs, despite the use of high-capacity transport services.

From the results of shipment-based pricing in the second part of Table 9, we can observe the trend of changes in profits, cost components, and service operation with the increase in the Ψ are broadly similar to the trend in the results of unified path-based pricing. One noticeable difference that can be seen is that the LSI maintains to operate truck services under the same proportion of 1:1:5:5 compared to the result under unified pricing. This is because it is profitable for the LSI to operate truck and railway services simultaneously due to the pricing flexibility.

Table 10
Sensitivity analysis of the increased levels of u_o^k for instance three.

Increased level (%)	Shipment proportion	Unified pricing profit (USD) (a)	Shipment-based pricing profit (USD) (b)	Profit difference % [(b − a)/a]	Average difference%
5	5:5:1:1	9.91×10^6	1.42×10^7	43.30%	33.86%
	3:3:3:3	1.59×10^7	2.31×10^7	45.30%	
	1:1:5:5	2.84×10^7	3.21×10^7	13.03%	
7.5	5:5:1:1	9.93×10^6	1.43×10^7	44.01%	34.46%
	3:3:3:3	1.64×10^7	2.39×10^7	45.73%	
	1:1:5:5	2.93×10^7	3.33×10^7	13.65%	
10 (baseline)	5:5:1:1	9.96×10^6	1.46×10^7	46.59%	35.59%
	3:3:3:3	1.69×10^7	2.46×10^7	45.56%	
	1:1:5:5	3.01×10^7	3.45×10^7	14.62%	
12.5	5:5:1:1	9.84×10^6	1.48×10^7	50.41%	38.22%
	3:3:3:3	1.73×10^7	2.52×10^7	45.66%	
	1:1:5:5	3.01×10^7	3.57×10^7	18.60%	
15	5:5:1:1	9.99×10^6	1.51×10^7	51.15%	38.27%
	3:3:3:3	1.77×10^7	2.60×10^7	46.89%	
	1:1:5:5	3.16×10^7	3.69×10^7	16.77%	

5.4.4. *The effect of the increased level of the total cost u_o^k of no-purchase option*

u_o^k is the generalized cost set for the no-purchase option for the shippers. The increased level of u_o^k significantly affects the obtained profits as it can bound the pricing. To track the effect of u_o^k on the profits obtained by the LSI with different proportions and pricing strategies, we increase the base value by the following percentages: 5%, 7.5%, 10%, 12.5%, and 15%.

Table 10 shows the optimal solutions of instance three with the five values of u_o^k. For each increased level, the LSI obtains higher profit differences with the proportion of 5:5:1:1 and 3:3:3:3 than 1:1:5:5, which shows the same trend as in the results obtained in Table 5. The last column of Table 10 shows that the average profit difference for each increased level is growing slightly with the increase of u_o^k. This is because the upper bounds for exiting the shippers market are higher, meaning that shippers are willing to spend more to purchase the transport services from the LSI, which leaves more freedom in pricing for the LSI.

6. Discussion and managerial implications

The numerical study reveals several relevant managerial findings for the LSI. Firstly, looking at the revenue management perspective, in case the LSI wants to implement a unified pricing strategy, our model can help to find the right trade-off price to obtain as much revenue as possible. A shipment-based pricing strategy can be very beneficial in a highly diversified market, substantially increasing the LSI's profit. Also, such a strategy can help the LSI reduce the variety of services. From the results, it turns out that with a unified pricing strategy, truck services need to be operated to keep attracting high-value shippers.

Interestingly, we also find that when the proportion of high-value shippers is higher, the LSI can increase the frequency of trains and maritime transport, and reduce the use of trucks. In this situation, economies of scale can be achieved while serving high-value shippers on time and with higher frequencies. When low-value shippers are dominant in the market, using trucks to serve high-value shippers is a better option.

Thirdly, the waiting time cost generated by the frequency delay can be seen as storage cost in practice. The model can help the LSI to find out the optimal service frequency decisions when facing storage cost fluctuations of containers in the market. In the context of multimodal transportation, the optimal frequency of each mode has a significant impact on the total transport time. Compared to rail transport, increasing the frequency of maritime transport is more important in handling high container storage costs due to the large service waiting times involved.

Fourthly, the penalty cost for unused capacity settings reflects the requirement of the LSI to limit the number of resources, due to, for example, high maintenance or rental costs. The values for this cost require an accurate analysis of the expenses for managing the different transport modes, in particular for high-capacity vehicles, whose cost structures can fluctuate more strongly than those of trucking, due to additional logistics costs involved.

Finally, the no-purchase option can indicate an alternative premium service that the shipper can choose, such as air transport or another LSI. If the price of this alternative is too low, the LSI has less room to differentiate the prices and attract more shippers and may even need to decide not to serve them.

7. Conclusions

In this paper, we presented a comprehensive joint service network design and pricing bi-level model, targeting the tactical planning of multimodal logistics service, which integrates the endogenous waiting time caused by frequency delay, competition from another substitute LSI with a cost advantage, and the shipper class with heterogeneous preferences considerations. The proposed framework aims to improve LSI's profits by designing the service network and implementing the shipment-based pricing strategy in the competitive transport market. To solve the bi-level model, we use the primal–dual optimality conditions and specific linearization methods to transfer the model into a single-level MILP model, which can be solved by commercial software. A case study conducted with a read-world network in the New Western Land-Sea Corridor in China is provided as a computational experiment for highlighting the proposed model. The sensitivity analysis of several key parameters was also conducted to provide further managerial insights.

The analysis of the computational results confirmed the correctness and applicability of the proposed joint service network design and pricing model. From the experiment, within a limited amount of computational time, optimal and good-quality feasible solutions are produced for realistic instances. The effectiveness of the shipment-based pricing for obtaining profits increases ranges from 5.93% to 49.95% in all shipment proportions when considering shippers with heterogeneous preferences is examined through experiments. The results also show that the service network design and pricing decisions of LSI are not only related to the cost of operations but also influenced by the competition from other transport alternatives and the features of customers. Therefore, investigating the competitors and the shipper proportion structure in the market can help the LSI to design a high-quality service network to attract more shippers and obtain higher profits. Moreover, the sensitivity analysis on the waiting time cost, the penalty cost, and the generalized cost of the no-purchase option not only prove the robustness of our proposed model, but also provides further managerial insights for practitioners on the design of the integrated multimodal transportation system.

This paper contains some limitations and future extensions could be done. First, in the proposed model we consider the exogenous competitive environment, which could not properly capture the reactions from the competitor. Future studies could be extended to a multi-leader-followers game model to investigate the interactions between the LSI and the competitor, or even among serval LSIs. Second, our paper considers fixed demands since we focus on the case of the offline-pricing problem on the tactical level, which may not be flexible enough to handle the uncertainties in certain scenarios. A further extension could be using robust optimization to consider the demand uncertainty, making the model more flexible and dynamic. Third, we focus on the service network design and pricing problem at the tactical level and use an industrial solver to solve the aggregated demand case. This approach may not be efficient when dealing with a larger number of OD pairs on a more operational level. We argue that tailored, exact algorithms for building feasible transport paths (e.g., column generation techniques) or heuristics should be developed for these large-scale real-world cases at the operational level.

CRediT authorship contribution statement

Zhenjie Wang: Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft; Writing – review & editing. **Dezhi Zhang:** Investigation, Data curation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Lóránt Tavasszy:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision. **Stefano Fazi:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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