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RESEARCH ARTICLE

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Two-stage stochastic programming with robust constraints for the logistics network post-disruption response strategy optimization

Abstract Logistics networks (LNs) are essential for the transportation and distribution of goods or services from suppliers to consumers. However, LNs with complex structures are more vulnerable to disruptions due to natural disasters and accidents. To address the LN post-disruption response strategy optimization problem, this study proposes a novel two-stage stochastic programming model with robust delivery time constraints. The proposed model jointly optimizes the new-line-opening and rerouting decisions in the face of uncertain transport demands and transportation times. To enhance the robustness of the response strategy obtained, the conditional value at risk (CVaR) criterion is utilized to reduce the operational risk, and robust constraints based on the scenario-based uncertainty sets are proposed to guarantee the delivery time requirement. An equivalent tractable mixed-integer linear programming reformulation is further derived by linearizing the CVaR objective function and dualizing the infinite number of robust constraints into finite ones. A case study based on the practical operations of the JD LN is conducted to validate the practical significance of the proposed model. A comparison with the rerouting strategy and two benchmark models demonstrates the superiority of the proposed model in terms of operational cost, delivery time, and loading rate.

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Keywords logistics network design, post-disruption response strategy, two-stage stochastic programming, conditional value at risk, robust constraint

1 Introduction

Logistics networks (LNs) are essential for the transportation and distribution of goods or services from suppliers to consumers (Mohammadi et al., 2016; Feng and Ye, 2021). According to the statistics of People's Daily (2022), LNs supported the delivery of more than 108 billion express packages in 2021, which were expected to have covered the express delivery services of all administrative villages in China. As an example, the JD LN consists of over 210 distribution centers (DCs), 7800 stations, over 1000 airlines, 300 rail lines, and tens of thousands of road lines. The JD LN provides a high-quality service guarantee for the customer satisfaction rate, e.g., during the "6·18" grand promotion, more than 200 cities could be reached in minutes, and 92% of districts and counties and 84% of villages were able to receive deliveries on the same day or the next day (JD Logistics Inc., 2021). However, LNs with complex structures are more vulnerable to disruptions due to natural disasters and accidents (Wang et al., 2021). For example, at the end of 2019, the outbreak of COVID-19 posed a great challenge to the operations of the JD LN. In particular, the lockdown of Wuhan City, which lasted for more than two months from January 23 to April 8 in 2020, caused over 1000 routes going through Wuhan City to be blocked, and over 13000 packages per day could not be distributed on time. System resilience emphasizes the system's ability to resist damage in a specific performance state or restore the system to its original performance state after a downgrade (Zuo, 2021). Supply chain resilience can be defined as "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function" (Ponomarov and Holcomb, 2009). Resilience strategies deal with high-impact events (Huang et al., 2017) and are mainly divided into two categories. One is the proactive strategies that have been investigated from various perspectives, such as network design, supplier selection, and redundancy. The other is reactive strategies, which are from the view of response and recovery and have not yet received sufficient attention (Premkumar et al., 2021). However, the self-adaptability and self-healing ability of the network in an unexpected disruption directly affect the core competitiveness of the network (Gao et al., 2021). Therefore, a cost-effective response strategy of rerouting and opening new lines in LNs for each package is vital to guarantee the customer satisfaction rate and maintain the advantages after disruptions.

To develop effective LN post-disruption response strategies, the following issues should be carefully investigated and addressed. First, for each affected package, an alternative route must be selected to recover the package delivery. Numerous packages and various candidate routes for packages complicate the route design. Second, new lines could be constructed for the post-disruption LN. Although this addition will increase the number of alternative routes, affected packages can be delivered via both new lines and original unaffected lines to find more chances of on-time delivery. Third, the routing decisions for packages are coupled, as the packages using the same lines will be aggregated and transported by selecting the optimal combination of vehicles. Thus, the response strategies should be optimized from the network perspective. Fourth, the uncertainty of transport demands between origin–destination (OD) pairs and transportation times over lines further complicates the problem. Specifically, when making the new-line-opening decision, the transport demands and transportation times are usually unknown uncertain factors, while the package rerouting decisions can be made adaptively after this information is fully revealed.

To address the problem of LN post-disruption response strategy optimization, this study proposes a novel two-stage stochastic programming (SP) model with robust delivery time constraints and conducts a case study based on the practical operations of the JD LN. The proposed model has the following salient features. First, the model considers the uncertainties of both transport demands and transportation times. To enhance the robustness of the obtained response strategy, the conditional value at risk (CVaR) criterion is utilized to reduce the operational risk due to uncertainty, and robust delivery time constraints based on the scenario-based uncertainty sets are proposed to guarantee the delivery timeliness in the face of post-disruption transportation time fluctuation. Second, in the first stage, the model determines the optimal new-line-opening decision, while the uncertain transport demands and transportation times are not disclosed. Then, the model is capable of making the optimal rerouting decisions and loading plans adaptively according to the realization of the uncertain factors. Third, to solve the proposed model, we adopt the sample average approximation approach to handle the random transport demands and provide an equivalent reformulation for the CVaR objective function. Furthermore, we equivalently reformulate the infinite number of robust constraints into a finite number of linear constraints and provide an equivalent tractable mixed-integer linear programming (MILP) reformulation.

The contributions of this study are summarized below. First, this research proposes a novel two-stage SP model with robust constraints that jointly optimizes the new-line-opening and rerouting decisions. The proposed model utilizes the CVaR criterion and robust constraints to improve the robustness of the response strategy. Second, we derive an equivalent tractable MILP reformulation for the proposed model by linearizing the CVaR objective function and dualizing the infinite number of robust constraints into finite ones. Finally, this study conducts a case study based on the practical operations of the JD LN, which not only validates the practical significance of the proposed model but also demonstrates its superiority over the rerouting strategy and two benchmark models in terms of operational cost, delivery time, and loading rate.

The remainder of this paper is organized as below. The literature review is presented in Section 2. The problem description and the mathematical models are given in Section 3. In Section 4, a case study is conducted. Finally, Section 5 provides conclusions and discusses future research directions.

2 Literature review

Several prevention and response strategies have been proposed to deal with disruptions from the "pre-disruption" and "post-disruption" perspectives, respectively (Medal et al., 2014; Ni et al., 2018; Manupati et al., 2022). This study considers the response strategies for post-disruption recovery in LNs. Thus, we only review related works in this area. Response strategies for different infrastructure networks, such as transportation networks (TNs), critical infrastructure networks (CINs), supply chain networks (SCNs), and LNs, share several common features. The disruption of TNs can cause passenger anxiety, traffic congestion, and even network disconnection (Khaled et al., 2015; Liu et al., 2022). Response strategies, such as traffic rerouting, critical blockage identification, and clearance, have been applied to restore transportation accessibility (Tuzun Aksu and Ozdamar, 2014;

Cacchiani et al., 2014). Khaled et al. (2015) maximized network resilience by optimizing the number of trains, routes, and blocks for freight rail infrastructures. In addition, Kasaei and Salman (2016) examined two arc routing problems for clearing blocked roads, where the first one minimizes the time to reconnect the road network and the second one maximizes the total benefit of the on-time reconnection of network components. Zou and Chen (2021) developed a bi-level decision-making framework for resilience-based recovery scheduling for the traffic environment with mixed autonomous fleets. Yin et al. (2017) modeled a new train rescheduling problem by considering backup trains for disruption recovery. Wang et al. (2022) formulated a mixed integer programming model to optimize reconfiguration strategies and operational solutions for traffic power systems coupled via grid-enabled electric vehicles. To mitigate the impacts of order backlog and delivery delay due to SCN disruption, response strategies, such as redundancy suppliers and transportation rerouting, have also been studied (Wang et al., 2016; Namdar et al., 2018; Ivanov, 2019). Ivanov (2021) investigated existing strategies in the context of the COVID-19 pandemic by using the discrete event simulation model. Moosavi and Hosseini (2021) proposed a quantitative resilience assessment based on simulation and proved the effectiveness of the extra-inventory preposition and backup supplier strategies. Typical post-disruption response strategies for the LNs include selecting backup hubs (Cheng et al., 2018; Kulkarni et al., 2022), switching shipping modes, and rerouting (Chen et al., 2016). For example, Peng et al. (2011) considered an LN design problem with the response strategy of opening a backup transshipment facility. Mohammadi et al. (2016) formulated a reliable hub location model for the disruption of LNs.

To handle uncertain post-disruption factors, such as recovery time, customer demand, and reusability (Fang and Sansavini, 2019; Das et al., 2022; Xu et al., 2022; Alkhaleel et al., 2022b), researchers usually adopt the two-stage optimization method with different risk measurement methods, such as the mean-risk (Alkhaleel et al., 2022a) or the risk-averse and risk-neutral (Alkhaleel et al., 2022b), where the uncertainties are characterized in terms of disruption scenarios and risk levels (Almoghathawi et al., 2019; Esmizadeh and Mellat Parast, 2021). For example, Khalili et al. (2017) presented a novel two-stage scenario-based mixed stochastic-possibilistic programming model for the integrated production and distribution planning problem in SCNs. To enhance supply chain resilience, Ni et al. (2018) proposed a two-stage SP model to reduce the cost of lost customers. Tolooie et al. (2020) probed the disruption risk of facilities and demand uncertainty and presented a two-stage stochastic mixed-integer programming model. Furthermore, Das et al. (2022) established a CVaR-based two-stage SP model to deal with the uncertainties of demand, available inventory, and level of reusability. Chen et al. (2016) developed three optimization models considering the response strategies of renting other carriers' capacities, reallocating local trucks, and prioritizing the order of shipments in inter-modal LNs. To deal with LN disruption, Cheng et al. (2018) adopted a two-stage robust optimization approach, where location decisions are first determined and recourse decisions are made after the disruptions are known. Chen et al. (2022) proposed a load redistribution mechanism for the restoration of LNs with two cascading failure scenarios. Wang et al. (2017) proposed a typical long-term strategic decision problem on SCN design with consideration to uncertain demands and deterministic equivalent model with nonanticipativity constraints; sample average approximation was adopted to analyze stochastic demands.

The aforementioned literature has enriched the understanding of post-disruption response strategies and uncertainty modeling techniques. Although the existing SCN resilience research on facility/hub location, links restoration, shipping modes selection, and rerouting strategies share several similarities with the problem in terms of considering the two-stage decision process and demand uncertainties (Peng et al., 2011; Mohammadi et al., 2016; Cheng et al., 2018; Kulkarni et al., 2022), few studies take the new-line-opening decision as the first-stage decision and consider the uncertainties of both transport demands and transportation times. Another focus of this study is to provide robust response strategies for practical operations. Table 1 presents a comparison with related studies in terms of network structures, response strategies, uncertainties, and optimization models.

Our research fills the research gap in the following three aspects. First, the response strategies investigated in the existing research are mostly from the perspective of nodes, i.e., backup hub selection or new hub opening. Meanwhile, our study proposes the joint response strategies of opening new lines and rerouting. Specifically, we propose a two-stage LN redesigning model that simultaneously optimizes the new-line-opening and rerouting decisions under the limited capacities of DCs. Second, to characterize the uncertain factors, few researchers have jointly investigated the uncertainties in demands and transportation times. This study further adopts the CVaR criterion and robust constraints to hedge against uncertain transport demands and transportation times, respectively. Third, this research conducts a case study based on the real-world operational scenario and data from the JD LN during the COVID-19 pandemic, which validates the practical significance of the proposed model.

3 Mathematical model and analysis

This section presents the proposed two-stage SP model and further provides an equivalent tractable reformulation

Table 1 Comparison with related studies

Literature	Network	Response strategies	Uncertainties	Optimization models
Khaled et al. (2015)	TN	Train design and re-routing		Deterministic model
Liu et al. (2022)		Passenger transit		Bi-level programming
Tuzun Aksu and Ozdamar (2014)		Links restoration		Integer programming
Kasaei and Salman (2016)		Clearing and repairing roads		Mixed-integer programming
Zou and Chen (2021)		Recovery scheduling		Bi-level programming
Alkhaleel et al. (2022b)	CIN	Restoration strategies	Repair time, transport time	Two-stage SP
Fang and Sansavini (2019)		Multi-model restoration	Repair time, resources	Two-stage SP
Xu et al. (2022)		Restoration	Repair time	Two-stage SP
Alkhaleel et al. (2022a)		Flexible restoration	Repair time, transport time	Two-stage SP
Manupati et al. (2022)	SCN	Replenishment scheme		Simulation
Medal et al. (2014)		Nearby-reallocation		Bi-objective programming
Ni et al. (2018)		Supply chain restoration	Potential facilities disruptions	Two-stage SP
Ivanov (2019)		Back-up contractors and capacity transfer		Simulation
Namdar et al. (2018)		Sourcing strategies	Facilities disruptions	SP
Wang et al. (2016)		Contingent rerouting		Simulation
Ivanov (2021)		Recovery and coordination		Simulation
Moosavi and Hosseini (2021)		Inventory prepositioning and supplier backup		Simulation
Cheng et al. (2018)		Resources reallocation	Facilities disruptions	Two-stage robust programming
Peng et al. (2011)		Backup transshipment facilities	Facilities disruptions	P-robustness model
Das et al. (2022)		Recourse decisions	Demand and pallets	Two-stage SP
Kulkarni et al. (2022)	LN	Back-up routes		Integer programming
Chen et al. (2016)		Switching shipping modes, resource renting and reallocating, and sequencing		Mixed-integer programming
Mohammadi et al. (2016)		Backup transshipment facilities	Hub disruptions	Nonlinear model
This paper		New-line opening and rerouting	Demand and transport time	Two-stage SP with robust constraints

by analyzing the properties of the CVaR criterion and robust constraints. Subsection 3.1 gives the problem description of the considered problem. Subsection 3.2 gives a basic deterministic model that neglects the uncertainties of transport demands and transportation times. To deal with the uncertainties, Subsection 3.3 proposes a two-stage SP with the CVaR objective function and robust delivery time constraints. Subsection 3.4 provides an equivalent tractable MILP reformulation for the proposed model.

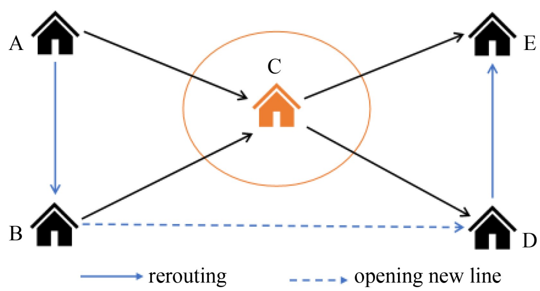


Fig. 1 Illustration of the response strategy.

3.1 Problem description

To recover the transport service for affected transport demands rapidly after a breakdown, the current research considers a joint response strategy of opening new lines and rerouting. We consider the following simple LN with five DCs, i.e., A, B, C, D, and E, and six original lines, i.e., A→B, A→C, B→C, C→D, C→E, and D→E (see Fig. 1). We suppose that four transport demands are delivered by this LN. Table 2 lists the original routes for the transport demands before the disruption. DC C is assumed to be disrupted, which makes the original routes for transport demands A→D, B→D, and B→E unavailable. In response to this disruption, the operator can open a new line B→D and reroute the paths for the affected transport demands A→D, B→D, and B→E. As listed in Table 2, after the disruption and opening the new line

Table 2 Transport demands and routes

Transport demands	Routes before disruption	Routes after disruption
A→B	A→B	A→B
A→D	A→C→D	A→B→D
B→D	B→C→D	B→D
B→E	B→C→E	B→D→E

B→D, the transport demands B→D can be delivered directly. Furthermore, this newly opened line can be used to transit the transport demands A→D and B→E. For example, the affected transport demand A→D is rerouted and transported via the new route A→B→D.

When the operator makes the new-lines-opening and rerouting decisions, the loading plan, i.e., types and the number of vehicles or volume of less-than-truckload (LTL) service used on each line, must be taken into account because the lower-level transportation cost is mainly affected by the aggregation of transport demands over different routes. For JD LN, six transportation modes can be divided into two categories: Full-truckload (FTL) transportation service and LTL transportation service. For FTL, five types of vehicles (with lengths of 5.2, 7.6, 9.6, 14.5, and 17.5 m, respectively) can be used, while only one type of transportation service corresponds to LTL. The selection of transportation modes and the new-line-opening decision should obey the following standard, as shown in Table 3. For example, when the length of the line is less than or equal to 500 km and the freight volume of demands delivered is no more than 100 m^3, only the vehicle with a length of 5.2 m can be used.

This study makes the following assumptions:

(1) The basic deterministic model commonly used by the practitioner takes the mean of uncertain transport demands and transportation times as a proxy. The proposed two-stage SP model explicitly considers these uncertainties.

(2) Transport demands with the same OD pair can be delivered by different routes to satisfy capacity constraints.

(3) To leverage the newly opened lines fully, the newly opened lines can be used to fulfill demands with different OD pairs as long as the capacity constraints are satisfied.

3.2 Basic deterministic model

The deterministic LN post-disruption response strategy optimization model aims to find the optimal new-line-opening, rerouting, and transportation mode selection decision to minimize the total setup cost of opening new lines and transportation cost while satisfying the on-time delivery requirement. The notations used in the following models are listed in Table 4.

We consider an LN that includes multiple DCs and lines. The set of DCs is K, and the transit capacity of DC

Table 3 The selection of different transportation modes

Volume (m^3)	Length (km)			
	⩽ 500	501–800	801–1500	⩾ 1501 km
< 100	5.2 m			
100–300	7.6 m	LTL		
300–400	9.6 m	9.6 m	LTL	
400–600	14.5 m	14.5 m	14.5 m	LTL
⩾ 600	17.5 m	17.5 m	17.5 m	17.5 m

$k \in K$ after disruption is S_k. L is the set of lines that includes a set of candidate new lines L_1 and a set of original lines L_2 that are still available after the disruption. For each line $l \in L$, its length is r_l. For each alternative new line $l \in L_1$, the minimum freight volume required to open l is Q_l, and the fixed cost of opening the new line l is q_l. I and J are the set of transport demands and the set of alternative routes, respectively. J_i is the set of candidate routes that can be selected by transport demand $i \in I$. The volume of transport demand $i \in I$ is presented as D_i. T_i is the average delivery time required by transport demand $i \in I$. The transportation time of route $j \in J$ is t_j. Whether transport demand $i \in I$ can be delivered by route $j \in J$ is indicated by a_{ij}. Each route consists of one or several lines. Whether route $j \in J$ passes through line $l \in L$ is indicated by b_{lj}. Meanwhile, whether route $j \in J$ passes through DC $k \in K$ is indicated by c_{jk}. $V = \{0, 1, ..., |V|\}$ is the set of transportation modes. $v = 0$ refers to the LTL transportation service, and $v = 1, ..., |V|$ represents a type of FTL vehicle. Each transportation mode $v \in V$ has a maximum capacity U_v, and the unit transportation cost is e_v. We use w_l to denote whether to open the new line $l \in L_1$. d_j denotes the volume of transport demand delivered on each route $j \in J$. Decision variables x_{lv} and y_l denote the number of vehicles $v \in V/\{0\}$ and the volume of LTL used on line $l \in L$, respectively.

Following the above notations, the basic deterministic model takes the following form:

$$(\mathrm{P}_0)\ \min_{w,d,x,y} \left\{ \sum_{l\in L}\sum_{v\in V/\{0\}} r_l e_v x_{lv} + \sum_{l\in L} r_l e_0 y_l + \sum_{l\in L_1} q_l w_l \right\}$$

$$s.t. \quad \sum_{j\in J} a_{ij} d_j = D_i,\ \forall i \in I, \tag{1}$$

$$\sum_{j\in J} a_{ij} d_j t_j \leqslant D_i T_i,\ \forall i \in I, \tag{2}$$

$$\sum_{j\in J} c_{jk} d_j \leqslant S_k,\ \forall k \in K, \tag{3}$$

$$\sum_{j\in J} b_{lj} d_j \geqslant Q_l w_l,\ \forall l \in L_1, \tag{4}$$

$$U_0 w_l \geqslant y_l,\ \forall l \in L_1, \tag{5}$$

Table 4 Notation list

Sets	Description
$K = \{1, ..., \lvert K\rvert\}$	Set of DCs
$L = \{1, ..., \lvert L\rvert\}$	Set of all lines; each line connects two adjoint DCs, $L = L_1 \cup L_2$
L_1	Set of candidate new lines; each corresponds to one transport demand
L_2	Set of unaffected original lines that are still available after the disruption
$I = \{1, ..., \lvert I\rvert\}$	Set of transport demands; each represents an OD pair
$J = \{1, ..., \lvert J\rvert\}$	Set of alternative routes; each represents a path between an OD pair
J_i	Set of alternative routes for the transport demand $i \in I$
$V = \{0, 1, ..., \lvert V\rvert\}$	Set of transportation modes; $v = 0$ represents the LTL transportation mode, and $v = 1, ..., \lvert V\rvert$ represents a type of FTL vehicle
Parameters	**Description**
$S_k \in \mathbb{R}_+$	The transit capacity of DC $k \in K$
$r_l \in \mathbb{R}_+$	The length of line $l \in L$
$Q_l \in \mathbb{R}_+$	The minimum volume required to open the new line $l \in L_1$
$q_l \in \mathbb{R}_+$	The fixed cost of opening the new line $l \in L_1$
$T_i \in \mathbb{R}_+$	The average delivery time requirement of transport demand $i \in I$
$D_i \in \mathbb{R}_+$	The freight volume of transport demand $i \in I$
$t_j \in \mathbb{R}_+$	The total transportation time of route $j \in J$
$a_{ij} \in \{0, 1\}$	Whether transport demand $i \in I$ can choose route $j \in J$; i.e., $J_i = \left\{j \in J : a_{ij} = 1\right\}$
$b_{lj} \in \{0, 1\}$	Whether route $j \in J$ passes through line $l \in l$
$c_{jk} \in \{0, 1\}$	Whether route $j \in J$ passes through DC $k \in K$
$e_0 \in \mathbb{R}_+$	The unit cost for transportation mode $v = 0$
$e_v \in \mathbb{R}_+$	The fixed cost for using one truck of mode $v \in V/\{0\}$
$U_v \in \mathbb{R}_+$	The maximum capacity of transportation mode $v \in V$
Decision variables	**Description**
$w_l \in \{0, 1\}$	Whether to open new line $l \in L_1$
$d_j \in \mathbb{R}_+$	The demand transported on route $j \in J$
$x_{lv} \in \mathbb{Z}_+$	The quantity of vehicle $v \in V/\{0\}$ used on line $l \in L$
$y_l \in \mathbb{R}_+$	The volume transported by the LTL service on line $l \in L$

$$w_l\left(\sum_{j\in J}\sum_{i\in I} b_{lj}a_{ij}D_i + \sum_{v\in V/\{0\}} U_v\right) \geqslant \sum_{v\in V/\{0\}} x_{lv}U_v + y_l,\ \forall l \in L_1, \quad (6)$$

$$\sum_{j\in J} b_{lj}d_j \leqslant \sum_{v\in V/\{0\}} x_{lv}U_v + y_l,\ \forall l \in L, \quad (7)$$

$$0 \leqslant y_l \leqslant U_0,\ \forall l \in L, \quad (8)$$

$$w \in \{0, 1\}^{L_1},\ d_j \in \mathbb{R}_+,\ x_{lv} \in \mathcal{X},\ y_l \in \mathcal{Y}, \quad (9)$$

where $\mathcal{X} = \{x \in \mathbb{Z}^{L\times V} : x_{lv} = 0, \forall (l, v) \in LV_1\}$ and $\mathcal{Y} = \left\{y \in \{0, 1\}^L : y_l = 0, \forall l \in L_b\right\}$. LV_1 is the set of line-vehicle combinations such that vehicle type v cannot be used on line l. Similarly, L_b refers to the set of lines that cannot use the LTL service. The sets LV_1 and L_b can be easily constructed from Table 3. Constraint (1) guarantees that the transport demand i needs to be completely delivered by its candidate routes. Constraint (2) ensures that the average delivery time requirement is satisfied for each transport demand. Constraint (3) ensures that the volume of transport demands that pass through DC k does not exceed its transit capacity. Constraint (4) ensures that the volume of transport demands on each newly opened line exceeds Q_l. Constraints (5) and (6) ensure that if the new line is not opened, the number of used vehicles and the quantity delivered by the LTL service should be zero. Constraint (7) enforces that the total transport demands on line l cannot exceed the maximum total capacity of all types of vehicles and the LTL service. Constraint (8) ensures that the quantity delivered by the LTL service is less than the maximum capacity of the LTL service.

The basic deterministic model is an MILP and thus can be solved directly by commercial solvers, such as CPLEX or Gurobi. Although the deterministic model is used by the practitioner in JD, it neglects the uncertain transport demands between OD pairs and uncertain transportation times over lines. Thus, in practice, the operator only uses this model to make long-term new-line-opening decisions by replacing the uncertain parameters with their mean values and resolves this model for the given new-line-opening decisions when the uncertain parameters are known. As shown in the following case study, the deterministic model usually leads to over-optimistic new-line-opening decisions, thus resulting in higher operational costs.

3.3 Two-stage stochastic programming model

The uncertainty of transport demands between OD pairs and transportation times over routes complicates the LN redesign problem. In this subsection, we propose a two-stage SP model with the CVaR objective function and robust delivery time constraints.

First, to deal with uncertain transported demands, we present a two-stage SP model, where $f(w, \tilde{D})$ denotes the second-stage transportation cost function for a given w and demand scenario $\tilde{D}$. Specifically, the operator needs to make the new-line-opening decision before the realization of uncertain factors, while the number of vehicles, the volume of LTL service, and the volume of demand transported on each route can be determined after the uncertainty is revealed. Moreover, to avoid an over-optimistic new-line-opening decision given by the expected cost criterion, we further adopt the CVaR criterion, which considers the expected performance under the worst-case scenario and thus is more suitable for risk-averse decision-makers.

For a random loss X, its α-level ($\alpha \in (0, 1]$) CVaR is defined as the expected value of X conditioning on $X \geqslant \mathrm{VaR}_\alpha(X)$, i.e., $\mathrm{CVaR}_\alpha(X) = \mathbb{E}[X \mid X \geqslant \mathrm{VaR}_\alpha(X)]$, where $\mathrm{VaR}_\alpha(X)$ denotes $1-\alpha$ quantile of X, i.e., $\mathrm{VaR}_\alpha(X) = \min\{z : F_X(z) \geqslant 1-\alpha\}$. Compared with $\mathrm{VaR}_\alpha(X)$, CVaR is a convex consistent risk measure and can be equivalently reformulated into the following minimization problem:

$$\mathrm{CVaR}_\alpha(X) = \min_z \left\{ z + \frac{1}{\alpha}\mathbb{E}[X - z]^+ \right\}, \tag{10}$$

where $[x]^+ = x$ if $x \geqslant 0$; otherwise, $[x]^+ = 0$. For the considered problem, we aim at minimizing the α-level CVaR of the random transportation cost $f(w, \tilde{D})$, i.e., $\mathrm{CVaR}_\alpha(f(w, \tilde{D}))$.

Second, to guarantee the delivery time service level, which is of vital importance to JD, we adopt the budget uncertainty set to characterize the uncertain transportation times and propose a set of robust delivery time constraints. Specifically, we suppose the set of the uncertain transportation time vector t lies in the following budget uncertainty set:

$$\mathcal{T} = \left\{ t : Lt_j \leqslant t_j \leqslant Ut_j,\ \sum_{j\in J} \frac{|t_j - \mu_j|}{\mu_j} \leqslant \delta,\ \forall j \in J \right\},$$

where μ_j denotes the mean transportation time over route j. Lt_j and Ut_j are lower and upper bounds for the transportation time over route j, respectively. The budget parameter δ controls the size of the uncertainty set. A larger value of δ leads to a more robust but conservative solution.

Based on the budget uncertainty set for the transportation times, we consider the following robust delivery time constraints for transport demand i, which guarantee the average delivery time requirement even in the worst-case scenario:

$$\sum_{j\in J} a_{ij} d_j t_j \leqslant D_i T_i,\ \forall t \in \mathcal{T}.$$

After the introduction of the CVaR objective function and the budget uncertainty set, the proposed two-stage LN redesign SP model with robust delivery time constraints takes the following form:

$$\text{(P)}\ \min_w \left\{ \mathrm{CVaR}_\alpha(f(w, \tilde{D})) + \sum_{l\in L_1} q_l w_l \mid w \in \{0, 1\}^{L_1} \right\},$$

where the second-stage transportation cost function $f(w, \tilde{D})$ is given as:

$$f(w, \tilde{D}) = \min_{d,x,y} \left\{ \sum_{l\in L} \sum_{v\in V/\{0\}} r_l e_v x_{lv} + \sum_{l\in L} r_l e_0 y_l \right\}$$

$$s.t. \quad \sum_{j\in J} a_{ij} d_j = D_i,\ \forall i \in I, \tag{11}$$

$$\sum_{j\in J} a_{ij} d_j t_j \leqslant D_i T_i,\ \forall i \in I,\ t \in \mathcal{T}, \tag{12}$$

$$\sum_{j\in J} c_{jk} d_j \leqslant S_k,\ \forall k \in K, \tag{13}$$

$$\sum_{j\in J} b_{lj} d_j \geqslant Q_l w_l,\ \forall l \in L_1, \tag{14}$$

$$U_0 w_l \geqslant y_l,\ \forall l \in L_1, \tag{15}$$

$$w_l \left(\sum_{j\in J} \sum_{i\in I} b_{lj} a_{ij} D_i + \sum_{v\in V/\{0\}} U_v \right) \geqslant \sum_{v\in V/\{0\}} x_{lv} U_v + y_l,\ \forall l \in L_1, \tag{16}$$

$$\sum_{j\in J} b_{lj} d_j \leqslant \sum_{v\in V/\{0\}} x_{lv} U_v + y_l,\ \forall l \in L, \tag{17}$$

$$0 \leqslant y_l \leqslant U_0,\ \forall l \in L, \tag{18}$$

$$d_j \in \mathbb{R}_+,\ x_{lv} \in \mathcal{X},\ y_l \in \mathcal{Y}. \tag{19}$$

The proposed two-stage SP model differs from the deterministic model in the following three aspects. First, the two-stage SP model uses the CVaR criterion to hedge against operational risk due to uncertainty. Second, we utilize robust constraints to ensure that for any transportation time vector in the budget uncertainty set, the required average delivery times are satisfied. Third, by adopting a two-stage optimization framework, the SP model can make robust new-line-opening decisions by fully considering the uncertain factors while keeping the rerouting and loading decisions adaptive to the realization of the uncertainties. Although the proposed SP model is a nonlinear mixed-integer program with an infinite number of constraints, next subsection gives an equivalent tractable reformulation by exploiting its structural properties.

3.4 Equivalent tractable reformulation

In this subsection, we provide an equivalent tractable reformulation for (P). We first analyze the CVaR objective function for a given first-stage decision w when the random transport demands have discrete probability distributions. Proposition 1 shows that the nonlinear CVaR objective function can be reformulated as a linear one.

Proposition 1. Suppose that the random transport demand vector $\tilde{D}$ has a discrete probability distribution with N scenarios, and each scenario has its probability $\mathrm{Prob}(\tilde{D}=D^n)=p^n$, $\sum_{n\in N}p^n=1$. Then, (P) can be reformulated into the following mixed-integer optimization problem:

$$(\mathrm{P_s})\ \min_{w,z,\psi^n,d^n,x^n,y^n}\left\{z+\frac{1}{\alpha}\sum_{n\in N}p^n\psi^n+\sum_{l\in L_1}q_lw_l\right\}$$

$$s.t.\quad \psi^n+z\geqslant\sum_{l\in L}\sum_{v\in V/\{0\}}r_le_vx_{lv}^n+\sum_{l\in L}r_le_0y_l^n,\ \forall n\in N, \tag{20}$$

$$\sum_{j\in J}a_{ij}d_j^n=D_i^n,\ \forall i\in I,\ \forall n\in N, \tag{21}$$

$$\sum_{j\in J}a_{ij}d_j^nt_j\leqslant D_i^nT_i,\ \forall i\in I,\ t\in\mathcal{T},\ \forall n\in N, \tag{22}$$

$$\sum_{j\in J}c_{jk}d_j^n\leqslant S_k,\ \forall k\in K,\ \forall n\in N, \tag{23}$$

$$\sum_{j\in J}b_{lj}d_j^n\geqslant Q_lw_l,\ \forall l\in L_1,\ \forall n\in N, \tag{24}$$

$$U_0w_l\geqslant y_l^n,\ \forall l\in L_1,\ \forall n\in N, \tag{25}$$

$$w_l\left(\sum_{j\in J}\sum_{i\in I}b_{lj}a_{ij}D_i^n+\sum_{v\in V/\{0\}}U_v\right)\geqslant\sum_{v\in V/\{0\}}x_{lv}^nU_v+y_l^n,\quad \forall l\in L_1,\ \forall n\in N, \tag{26}$$

$$\sum_{j\in J}b_{lj}d_j^n\leqslant\sum_{v\in V/\{0\}}x_{lv}^nU_v+y_l^n,\ \forall l\in L,\ \forall n\in N, \tag{27}$$

$$0\leqslant y_l^n\leqslant U_0,\ \forall l\in L,\ \forall n\in N, \tag{28}$$

$$w\in\{0,\ 1\}^{L_1},\ z\in\mathbb{R},\ \psi^n\in\mathbb{R}_+,\ d_j^n\in\mathbb{R}_+,\ x_{lv}^n\in\mathcal{X},\ y_l^n\in\mathcal{Y}. \tag{29}$$

Proof.

From the equivalent definition of CVaR, we have:

$$\mathrm{CVaR}_\alpha(f(w,\ \tilde{D}))=\min_{z\in\mathbb{R}}\left\{z_i+\frac{1}{\alpha}\mathbb{E}_{\mathbb{P}}[\max\{f(w,\ \tilde{D})-z,\ 0\}]\right\}.$$

Therefore, the objective function of (P) can be reformulated as :

$$\min_{w,z}\left\{z+\frac{1}{\alpha}\mathbb{E}_{\mathbb{P}}[\max\{f(w,\ \tilde{D})-z,\ 0\}]\right\}=\min_{w,z}\left\{z+\frac{1}{\alpha}\sum_{n\in N}p^n\max\{f(w,\ \tilde{D})-z,\ 0\}\right\}.$$

Let $\psi^n=\max\{f(w,\ \tilde{D}^n)-z,\ 0\}$. Thus, (P) can be further reformulated as:

$$\min_{w,z,\psi}\left\{z+\frac{1}{\alpha}\sum_{n\in N}p^n\psi^n+\sum_{l\in L_1}q_lw_l\right\}$$

$$s.t.\quad \psi^n\geqslant f(w,\ \tilde{D}^n)-z,\ \forall n\in N,$$

$$\psi^n\geqslant 0,\ \forall n\in N,$$

$$w\in\{0,\ 1\}^{L_1},\ z\in\mathbb{R}.$$

From the definition of the second-stage objective function f, for any scenario n, the constraint $\psi^n\geqslant f(w,\ \tilde{D}^n)-z$ is equivalent to the following ones:

$$\psi^n+z\geqslant\sum_{l\in L}\sum_{v\in V/\{0\}}r_le_vx_{lv}^n+\sum_{l\in L}r_le_0y_l^n,$$

$$\sum_{j\in J}a_{ij}d_j^n=D_i^n,\ \forall i\in I,$$

$$\sum_{j\in J}a_{ij}d_j^nt_j\leqslant D_i^nT_i,\ \forall i\in I,\ t\in\mathcal{T},$$

$$\sum_{j\in J}c_{jk}d_j^n\leqslant S_k,\ \forall k\in K,$$

$$\sum_{j\in J}b_{lj}d_j^n\geqslant Q_lw_l,\ \forall l\in L_1,$$

$$U_0w_l\geqslant y_l^n,\ \forall l\in L_1,$$

$$w_l\left(\sum_{j\in J}\sum_{i\in I}b_{lj}a_{ij}D_i^n+\sum_{v\in V/\{0\}}U_v\right)\geqslant\sum_{v\in V/\{0\}}x_{lv}^nU_v+y_l^n,\ \forall l\in L_1,$$

$$\sum_{j\in J}b_{lj}d_j^n\leqslant\sum_{v\in V/\{0\}}x_{lv}^nU_v+y_l^n,\ \forall l\in L,$$

$$0\leqslant y_l^n\leqslant U_0,\ \forall l\in L,$$

$$d_j^n \in \mathbb{R}_+,\ x_{lv}^n \in \mathcal{X},\ y_l^n \in \mathcal{Y},$$

which completes the proof.

To characterize the dependence between the uncertain transportation times and transport demands, we adopt the following scenario-based uncertainty set to describe the transportation times under a specific scenario n:

$$\mathcal{T}^n = \left\{ t^n : Lt_j^n \leqslant t_j^n \leqslant Ut_j^n,\ \sum_{j\in J} \frac{\left|t_j^n - \mu_j^n\right|}{\mu_j^n} \leqslant \delta^n,\ \forall j \in J \right\},$$

where μ_j^n denotes the mean transportation time over route j. Lt_j^n and Ut_j^n are the lower and upper bounds for the transportation time over route j for a given transport demand scenario n, respectively. The budget parameter δ^n determines the size of the budget set in scenario n. When the parameters $(\mu_j^n, Lt_j^n, Ut_j^n)$ are identical for all scenarios, the transportation time is independent of the transport demand. Moreover, when the size parameters of the uncertain sets are zero, i.e., $\delta^n = 0$, the extended model is reduced to the classical two-stage scenario-based SP model.

Next, we simplify the robust delivery time constraints. The following proposition shows that an infinite number of robust constraints can be equivalently reformulated into a finite number of linear constraints by the strong duality.

Proposition 2. For any $i \in I$, $n \in N$, the robust delivery time constraints can be equivalently reformulated into the following linear constraints:

$$\delta^n \lambda_i^n + \sum_{j\in J_i} \mu_j^n \left(u_j^n - v_j^n\right) - \sum_{j\in J_i} Lt_j^n \gamma_j^n + \sum_{j\in J_i} Ut_j^n \beta_j^n \leqslant D_i^n T_i,$$

$$\mu_j^n \left(u_j^n + v_j^n\right) = \lambda_i^n,\ \forall j \in J_i,$$

$$a_{ij} d_j^n = u_j^n - v_j^n + \beta_j^n - \gamma_j^n,\ \forall j \in J_i,$$

$$\gamma_j^n,\ \beta_j^n,\ u_j^n,\ v_j^n,\ \lambda_i^n \geqslant 0,\ \forall j \in J_i.$$

Proof.

For any $i \in I$, $n \in N$, the robust delivery time constraints are equivalent to the following constraints:

$$\text{(RC1)}\ \max_{t^n} \left\{ \sum_{j\in J} a_{ij} d_j^n t_j^n : t^n \in \mathcal{T}^n \right\} \leqslant D_i^n T_i.$$

By introducing an auxiliary variable $z_j^n \geqslant \left|t_j^n - \mu_j^n\right|$, the problem (RC1) can be equivalently reformulated as the following linear programming problem:

$$\text{(RC2)}\ \max_{t^n, z^n} \left\{ \sum_{j\in J} a_{ij} d_j^n t_j^n = \sum_{j\in J_i} d_j^n t_j^n : Lt_j^n \leqslant t_j^n \leqslant Ut_j^n,\ z_j^n \geqslant t_j^n - \mu_j^n,\ z_j^n \geqslant \mu_j^n - t_j^n,\ \forall j \in J,\ \sum_{j\in J} \frac{z_j^n}{\mu_j^n} \leqslant \delta^n \right\}.$$

Let (t^{n*}, z^{n*}) be the optimal solution of (RC2). We have $t_j^{n*} = \mu_j^n$ and $z_j^{n*} = 0$ for any $j \notin J_i$, where $J_i = \{j \in J : a_{ij} = 1\}$. Thus, (RC2) can be further reduced to the following:

$$\text{(RC3)}\ \max_{t^n, z^n} \left\{ \sum_{j\in J_i} d_j^n t_j^n : Lt_j^n \leqslant t_j^n \leqslant Ut_j^n,\ z_j^n \geqslant t_j^n - \mu_j^n,\ z_j^n \geqslant \mu_j^n - t_j^n,\ \forall j \in J_i,\ \sum_{j\in J_i} \frac{z_j^n}{\mu_j^n} \leqslant \delta^n \right\}.$$

By introducing dual variables $\gamma_j^n, \beta_j^n, u_j^n, v_j^n \geqslant 0$ $(j \in J_i)$ and $\lambda_i^n \geqslant 0$ for constraints of (RC3), we obtain the dual problem of (RC3) as follows, and the strong duality holds:

$$\min_{\gamma^n, \beta^n, u^n, v^n, \lambda^n} \left\{ \delta^n \lambda_i^n + \sum_{j\in J_i} \mu_j^n \left(u_j^n - v_j^n\right) - \sum_{j\in J_i} Lt_j^n \gamma_j^n + \sum_{j\in J_i} Ut_j^n \beta_j^n \right\} \leqslant D_i^n T_i$$

$$\text{s.t.}\quad \mu_j^n \left(u_j^n + v_j^n\right) = \lambda_i^n,\ \forall j \in J_i,$$

$$a_{ij} d_j^n = u_j^n - v_j^n + \beta_j^n - \gamma_j^n,\ \forall j \in J_i,$$

$$\gamma_j^n,\ \beta_j^n,\ u_j^n,\ v_j^n,\ \lambda_i^n \geqslant 0,\ \forall j \in J_i.$$

Thus, the robust delivery time constraints are equal to the following ones:

$$\delta^n \lambda_i^n + \sum_{j\in J_i} \mu_j^n \left(u_j^n - v_j^n\right) - \sum_{j\in J_i} Lt_j^n \gamma_j^n + \sum_{j\in J_i} Ut_j^n \beta_j^n \leqslant D_i^n T_i,$$

$$\mu_j^n \left(u_j^n + v_j^n\right) = \lambda_i^n,\ \forall j \in J_i,$$

$$a_{ij} d_j^n = u_j^n - v_j^n + \beta_j^n - \gamma_j^n,\ \forall j \in J_i,$$

$$\gamma_j^n,\ \beta_j^n,\ u_j^n,\ v_j^n,\ \lambda_i^n \geqslant 0,\ \forall j \in J_i.$$

From Propositions 1 and 2, (P) can be equivalently reformulated into a deterministic MILP, which can be solved directly by commercial solvers, i.e., CPLEX and Gurobi.

Proposition 3. The two-stage LN redesign stochastic model (P) is equivalent to the following problem:

$$\text{(SP-RC)}\ \min_{w,z,\psi,d,x,y,\gamma,\beta,u,v,\lambda} \left\{ z + \frac{1}{\alpha} \sum_{n\in N} p^n \psi^n + \sum_{l\in L_1} q_l w_l \right\}$$

$$\text{s.t.}\quad \delta^n \lambda_i^n + \sum_{j\in J_i} \mu_j^n \left(u_j^n - v_j^n\right) - \sum_{j\in J_i} Lt_j^n \gamma_j^n + \sum_{j\in J_i} Ut_j^n \beta_j^n \leqslant D_i^n T_i,\quad \forall i \in I,\ \forall n \in N,$$

$$\mu_j^n\left(u_j^n+v_j^n\right)=\lambda_i^n,\ \forall j\in J_i,\ \forall i\in I,\ \forall n\in N,$$

$$a_{ij}d_j^n=u_j^n-v_j^n+\beta_j^n-\gamma_j^n,\ \forall j\in J_i,\ \forall i\in I,\ \forall n\in N,$$

$$\gamma_j^n,\ \beta_j^n,\ u_j^n,\ v_j^n,\ \lambda_i^n\geqslant 0,\ \forall j\in J_i,\ \forall i\in I,\ \forall n\in N,$$

Constraints (20), (21), (23)–(29).

4 Case Study

This section conducts a case study based on historical data from the JD LN. Subsection 4.1 gives the numerical setting. Subsections 4.2 and 4.3 report the computational results of comparison with the rerouting strategy and benchmark models, respectively. Subsection 4.4 conducts the sensitivity analysis of model parameters.

4.1 Numerical setting

To analyze the effect of Wuhan lockdown that lasted for more than two months from January 23 to April 8, 2020 on JD LN, we focus on the network around Hubei province in the Central China area. As shown in Fig. 2, in the considered area, JD LN has 14 DCs, and the DC located in Wuhan indexed by 0 is the critical hub node in this area before the disruption caused by the pandemic.

After the disruption, the remaining 13 OD pairs had 78 transport demands. As a result of the Wuhan lockdown, 40 transport demands among OD pairs that were originally connected by the DC in Wuhan were affected. The original routes for the other 38 transport demands not transiting via the DC in Wuhan were still available after the disruption. For each affected transport demand, we introduce a new direct route. Thus, the considered LN has 78 lines and 284 candidate routes in total.

The transit capacity of each DC k is between 4000 m^3 and 10000 m^3. Based on historical data, we generate transport demand scenarios according to the independent truncated normal distribution by matching its mean, variance, and lower bound to historical statistics. In general, the mean of each transport demand i is between 200 m^3 and 800 m^3, and the standard deviation of each transport demand is within 30% of the mean. We generate the scenario-based uncertainty sets of the uncertain transportation times similarly based on the historical transportation time samples.

The fixed setup cost of opening a new line $l\in L_1$ is 2000 yuan because it is mainly made of the standardized platform construction cost. The unit LTL freight service cost is 0.35 yuan/m^3, and its maximum service capacity is 10000 m^3. The transportation capacity and cost for FTL vehicles are given in Table 5.

All the computations are performed on a personal computer with Intel (R) Core (TM) i7-10510U CPU and 16 GB memory. The optimization problems are solved by Gurobi 9.5.1 solver coded in MATLAB 2021b.

4.2 Comparison with the rerouting strategy

In this subsection, we compare the proposed joint new-line-opening and rerouting strategy with the rerouting strategy. Specifically, we use SP-RC to denote the proposed model that adopts the CVaR objective function and robust constraints. The optimization model for the

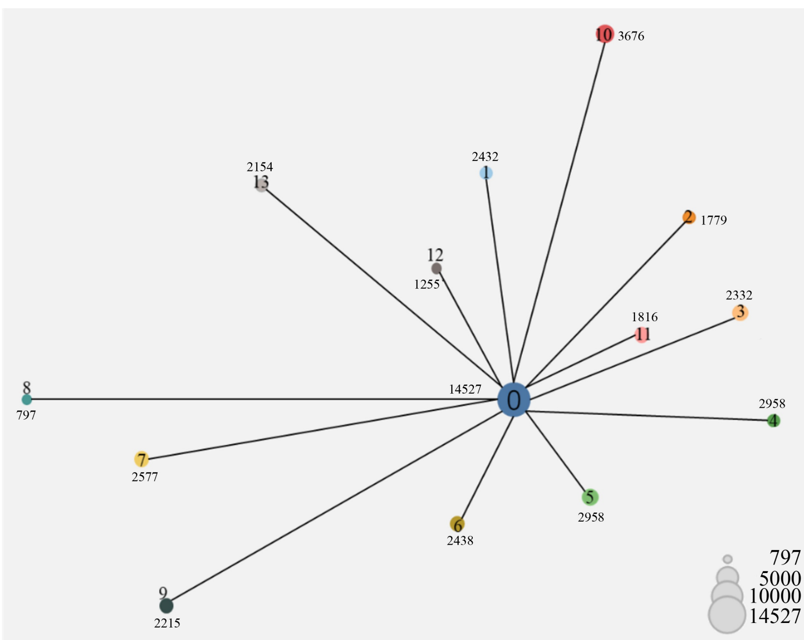


Fig. 2 The daily transport demands of DCs in JD LN before the disruption.

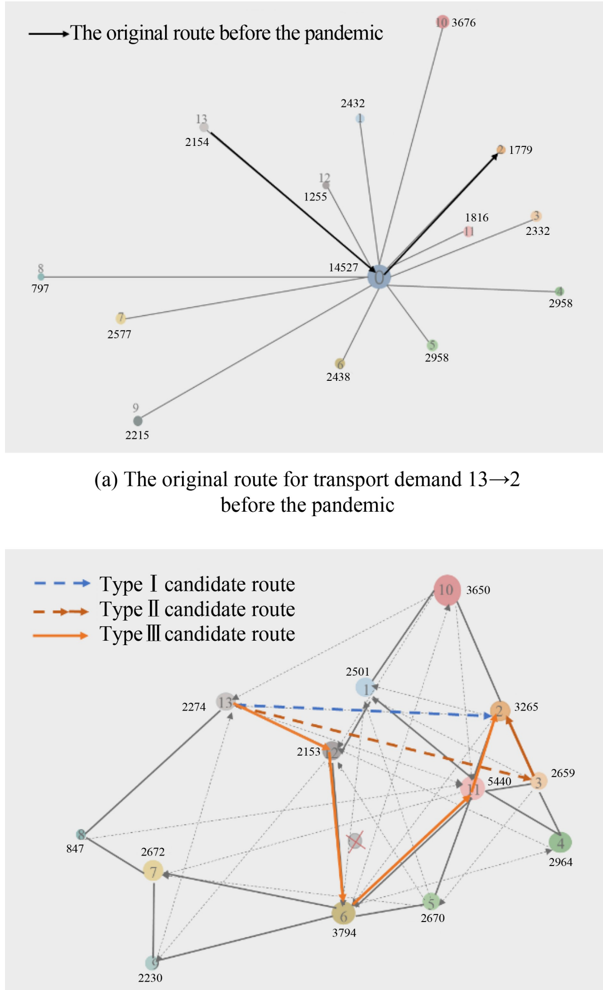
Table 5 Transportation capacity and cost for FTL vehicles

No.	Type	Capacity (m^3)	Cost (yuan/m^3)
1	17.5 m	123	30.75
2	14.5 m	90	24.30
3	9.6 m	56	16.24
4	7.6 m	40	12.00
5	5.2 m	21	6.51

rerouting strategy corresponds to SP-RC with $L_1 = \varnothing$. We report the computational results of both models with $\alpha = 0.05$ and $\delta = 0.25$ in terms of cost, delay time, and loading rate in Table 6. First, compared with the rerouting strategy, although the joint strategy leads to a higher new line setup cost, it reduces both the average transportation cost and the total cost by 11.94% and 11.22%, respectively. Thus, the joint response strategy is a more effective method for recovery from the disruption event than the single response strategy in terms of reducing the total operational cost.

Second, in terms of delivery time, the joint response strategy also outperforms the single response strategy by reducing the delay time by 13.86%. As transportation times are proportional to distances of routes, we further investigate the driving force for this reduction by analyzing the alternative routes of the proposed model. Figure 3 illustrates the routes for transport demand 13→2 before and after the pandemic under the joint strategy. Notably, the original route for transport demand 13→2 is not available when the DC in Wuhan is disrupted. However, the proposed joint strategy is capable of providing three types of candidate routes for transport demand 13→2, where the type I candidate route is the newly opened direct line, the type II candidate route consists of both newly opened and original lines, and the type III candidate route consists only of the original lines. Thus, the joint response strategy is capable of providing more diverse alternatives, which are of great value in an uncertain environment.

Finally, the joint response strategy also outperforms the single response strategy by increasing the loading rate by 59.18%. Figure 4 illustrates the optimal solution under the joint response strategy. Specifically, Fig. 4(a) depicts the six lines with more than 750 m^3 freight volume, where five of them (dashed line) are newly opened lines.



(a) The original route for transport demand 13→2 before the pandemic

(b) The candidate routes for transport demand 13→2 after the pandemic under the joint strategy

Fig. 3 The routes for transport demand 13→2 before and after the pandemic.

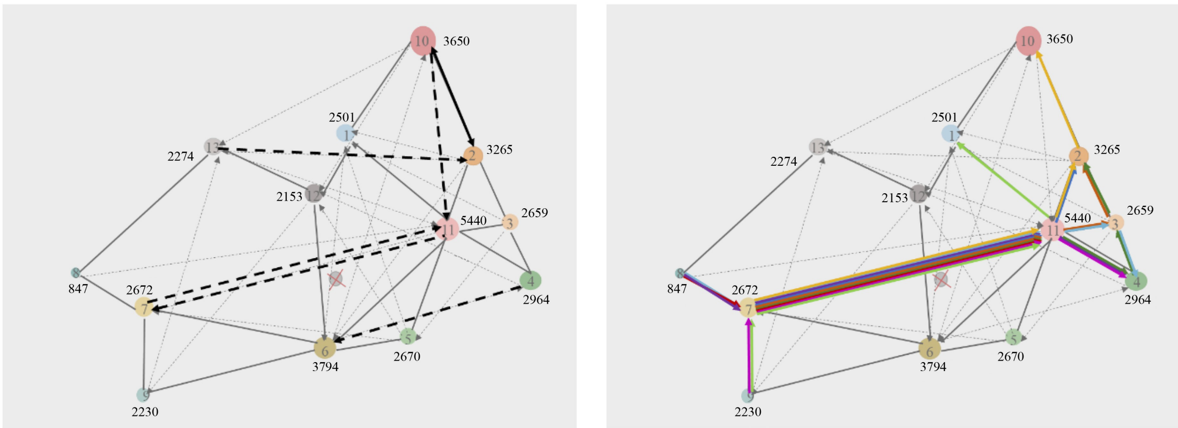
Figure 4(b) shows that the newly opened line 7→11 is used by multiple routes. From Fig. 4, we conclude that the proposed model can jointly optimize the new-line-opening and rerouting decisions such that the newly opened lines have a higher loading rate.

4.3 Comparison with other benchmark models

In this subsection, we compare the SP-RC model with the

Table 6 The comparison between characteristics of two solutions

Characteristics	SP-RC with $L_1 = \varnothing$	SP-RC	Δ (%)
Fixed cost of opening new lines (yuan)	0.00	46000.00	–
Average transportation cost (yuan)	6446668.64	5677243.42	−11.94
Total cost (yuan)	6446668.64	5723243.42	−11.22
Average delay time (h)	2.67	2.30	−13.86
Average loading rate	0.49	0.78	59.18



(a) The lines with more than 750 m³ freight volume

(b) The routes that use the line 7→11

Fig. 4 Illustration of the optimal solution under the joint response strategy.

Table 7 Comparison among the SP-RC, DM, and SP models

Performance indices	SP-RC	DM	Δ (%)	SP	Δ (%)
Fixed cost of opening new lines (yuan)	46000.0	40000.0	15.00	42000.0	9.52
Average transportation cost (yuan)	5683362.7	5818490.5	−2.32	5684262.5	−0.02
CVaR of transportation cost (yuan)	6053884.3	6312730.0	−4.10	6056358.6	−0.04
Total cost (yuan)	5729362.7	5858490.5	−2.20	5726262.5	0.05
Average delay time (h)	2.30	2.36	−2.54	2.32	−0.86
Average delay time of delayed demands (h)	3.57	3.69	−3.25	3.61	−1.11
Average loading rate	0.78	0.74	5.41	0.76	2.63
Total transit times	71.25	75.91	−6.14	73.15	−2.60

two benchmark models. One benchmark is the deterministic model (DM) given in Subsection 3.2. Another one is the two-stage SP model without robust constraints (SP). Table 7 reports the performance of the three models in terms of cost, loading rate, and delay time. The relative improvement Δ made by the SP-RC model that we have proposed is also given. First, we observe that the SP-RC model is inclined to open more new lines and thus leads to a higher fixed cost. By opening more new lines, the SP-RC model is able to reduce the total transportation cost compared with the DM and SP models. In terms of the total cost, the SP-RC model outperforms the DM model and is comparable to the SP model. Second, the SP-RC model is superior to both DM and SP models in terms of delay time. For example, the SP-RC model reduces the average delay time of delayed demands of the DM and SP models by 3.25% and 1.11%, respectively. Another advantage of the proposed SP-RC model is that it can improve the loading rate and reduce transit times. As illustrated in Fig. 4, although the SP-RC model opens more new lines, the newly opened lines are usually used by multiple routes and thus have a higher loading rate. In terms of total transit times, the SP-RC model also improves the performance of the DM and SP models by 6.14% and 2.60%, respectively.

Next, we compare the computational times of the four models, i.e., the SP-RC, SP-RC with $L_1 = \varnothing$, DM, and SP models. All these models are solved by the Gurobi solver. The running time limit is 5 hours (i.e., 18000 s), and the tolerance relative gap is selected as 0.1%. Table 8 reports the average computational performances of different models over 10 randomly generated instances. We can see that both SP-RC and SP models are time consuming and reach the running time limit, while the SP-RC with $L_1 = \varnothing$ model can be solved efficiently in minutes. The Gurobi solver also takes nearly two hours to obtain a near-optimal solution for the DM model within 0.1% relative gap. However, as shown in Table 8, when the first-stage new-line-opening decisions are given, the second-stage routing and loading plan decisions for a scenario

Table 8 Computation times of different models

Model	Run time (s)	Gap (%)
SP-RC	18000	0.660
Second-stage problem for a scenario	199.52	0.090
SP-RC with $L_1 = \varnothing$	1179.63	0.098
DM	6905.88	0.097
SP	18000	0.510

can be easily optimized. The first-stage new-line-opening decisions are medium-term response strategies and cover a span of weeks, and the second-stage decisions are made when the uncertain scenario is realized. Thus, the proposed models are practical in providing timely operational decisions for operators.

4.4 Sensitivity analysis

This subsection reports on the sensitivity analysis of critical parameters for the proposed SP-RC model.

Effect of fixed cost q. Figure 5(a) illustrates the performance of the SP-RC model under different values of the fixed cost q. Figure 5(a) shows that as the fixed cost increases, the total cost and transportation cost also increase in general. This observation is consistent with the intuition that the operator can always benefit from reducing the fixed cost of opening new lines.

Effect of the average delivery time requirement T. A smaller average delivery time requirement indicates a shorter delivery time and thus a higher level of customer service. To calibrate the effect of the average delivery time requirement, we normalize its value by the mean delivery time among all candidate routes. Figure 5(b) shows that, in general, the average delivery time requirement has a threshold effect on the cost, which suggests that the operator is able to select the best delivery time requirement parameter by conducting the sensitivity analysis.

Effect of the minimum volume required Q to open new lines. Figure 5(c) shows the performance of the SP-RC model under different normalized values of Q. We observe that setting a higher value of Q always leads to a higher operational cost. The operator should balance the practical operation regulations and the operational cost when selecting the value of Q.

Effect of risk-averse α-level. Figure 5(d) reports the performance of the SP-RC model under different risk-averse levels. From Fig. 5(d), we observe that the operational cost always increases as the value of α increases.

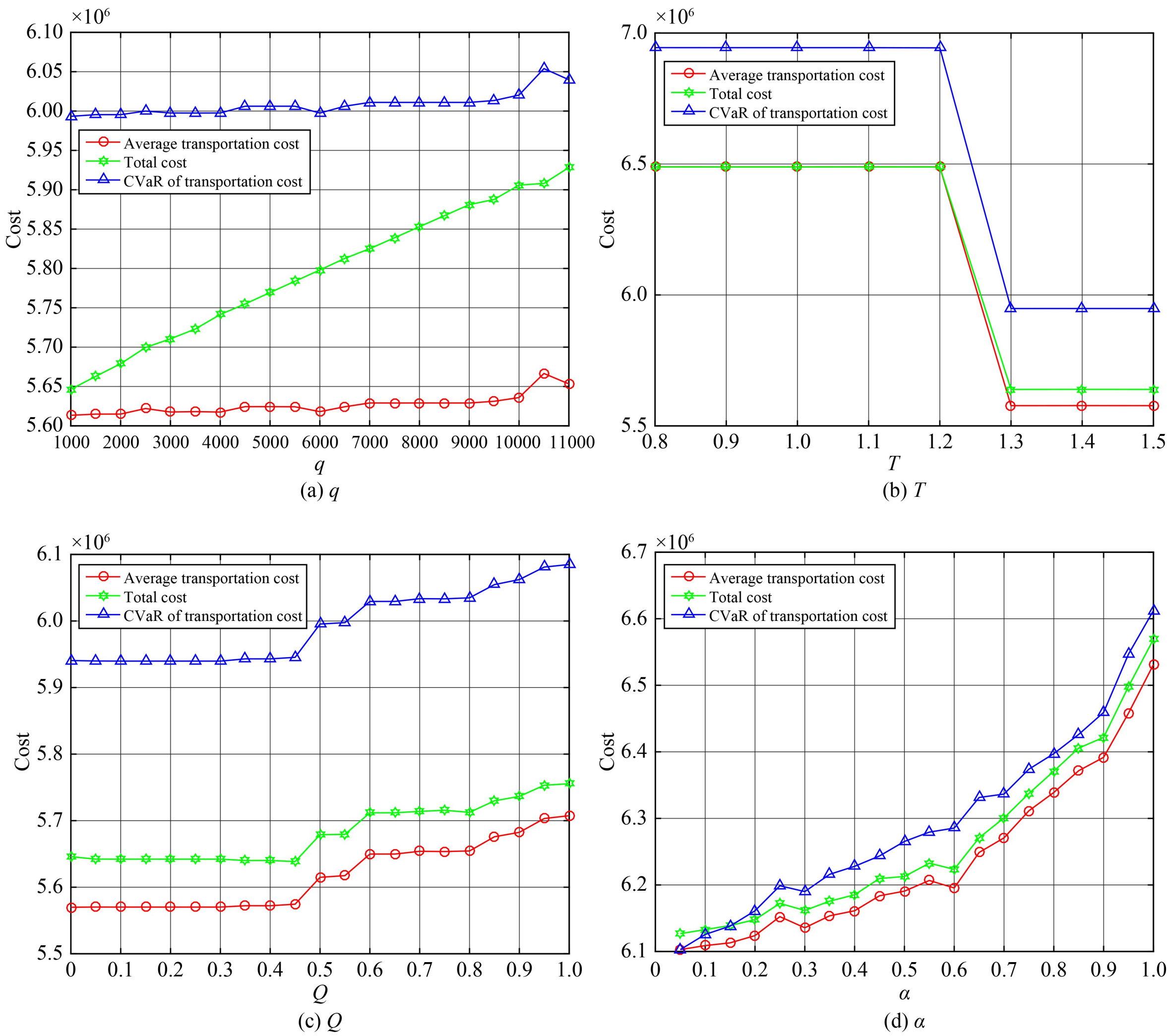


Fig. 5 The impact of parameters on the operational cost.

As α approaches 0, the CVaR of transportation cost coincides with the average cost. This outcome is consistent with the definition of CVaR as $\mathrm{CVaR}_0(X) = \mathbb{E}[X]$. As α approaches 1, the operational cost increases rapidly. Figure 5(d) suggests that the operators' risk preferences should be carefully calibrated to avoid over-conservative decisions.

5 Conclusions

This study investigates the joint new-line-opening and rerouting response strategy for LNs under disruption in the express industry. This research proposes a novel two-stage SP model with robust delivery time constraints. In the first stage, the proposed model aims at finding robust new-line-opening decisions in the face of uncertain transport demands and transportation times by minimizing the CVaR criterion and considering the robust delivery time constraints. In the second stage, the proposed model is capable of selecting the optimal routes and loading plans when the uncertainties are fully disclosed. We derive an equivalent tractable MILP reformulation for the proposed model by linearizing the CVaR objective function and dualizing the infinite number of robust constraints into finite ones. We further conduct a case study based on the historical data of the JD LN when the pandemic hit Wuhan. The case study shows that the LN can greatly benefit from jointly optimizing the new-line-opening and rerouting decisions in comparison with single rerouting strategy. Moreover, although the proposed SP-RC model is inclined to open more new lines, it outperforms both the DM and SP models in terms of delay time and loading rate. The operational cost given by the SP-RC model is superior to that of the DM model and is comparable with that of the SP model. A sensitivity analysis is conducted to provide suggestions on parameter calibration for the LN operators.

The proposed model adopts scenario-based uncertainty sets to describe the uncertain transportation times and imposes robust delivery time constraints to guarantee delivery time requirements. However, the robust approach may lead to conservative solutions. One way to reduce the conservativeness of robust optimization is to consider more distributional information and use the distributionally robust optimization approach (Zhang et al., 2022). Another future research direction is to design a more efficient customized algorithm for the equivalent MILP reformation by exploiting its structural properties.

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