A two-stage stochastic winner determination model integrating disruption mitigation strategies for transportation service procurement auctions

Abstract

This paper studies a revised winner determination problem with disruptions for a fourth party logistics (4PL) provider. Integrating a hybrid disruption mitigation strategy that includes fortification, reservation and outside options into combinatorial reverse auctions, a new two-stage stochastic winner determination model is constructed. Developing a scenario reduction approach to obtain representative scenarios for the deterministic equivalent reformulation, we use the CPLEX solver for solution method. Numerical experiments illustrate the effectiveness and applicability of the proposed model and method. Comparison analysis indicates that our strategy is dominant, and thus could be a useful tool for the 4PL provider to handle disruptions.

Keywords: Winner determination; disruption mitigation strategy; transportation service procurement; combinatorial reverse auction

1. Introduction

With the development of information technology and the global economy, many manufacturing firms have witnessed changes from being "insourcing" to being "outsourcing" in their logistics activities in recent years. This is because outsourcing logistics-related activities to other third party logistics (3PL) providers, enterprises can obtain advantages, such as only focusing on the core business, reducing operating costs, improving productivity and efficiency, and gaining access to unavailable resources (Tao et al., 2017). As reported by a leading supply chain knowledge market and research firm (Armstrong & Associates), the global 3PL revenue expanded to $802.2 billion in 2016[1]. Yet, with the growing expansion of the logistics market and the increasingly complex supply network, the requirement of customers may sometimes go beyond a single 3PL's capability that lacks integration of technology, transportation services and warehousing resources (Christopher, 2011). In such situations, there is a need for an organization to strategically combine focal 3PLs with technology companies, experienced consulting firms and other resource providers to run comprehensive logistics services across the entire supply chain; referred to as a fourth party logistics (4PL) provider. A 4PL is defined as an integrator that assembles the resources, capability, and technology of its own organization and other organizations to design, build, and run comprehensive supply chain solutions (Huang et al., 2013). For example, the Adage Logistics Company[2], a Chinese logistics enterprise, has positioned itself as a 4PL that provides integrated logistics services for manufacturers, retailers, and distributors by managing 3PLs and other resources. In practice, adopting

[1] http://www.3plogistics.com/3pl-market-info-resources/3pl-market-information/global-3pl-market-size-estimates/

[2] http://www.adagelogistics.com

the 4PL model can increase the supply chain efficiency, reduce logistics costs and lower carbon emissions for enterprises (Tao et al., 2017).

Due to the advantage of cost minimization and service performance improvement (Caplice & Sheffi, 2003; Holland & O'Sullivan, 2005; Sheffi, 2004), the combinatorial reverse auction (CRA) could be a useful tool adopted by the 4PL for transportation service procurement (TSP) from 3PLs under the context of Internet commerce. In such an auction, a 4PL acting as an auctioneer would solicit bids from a group of 3PLs, and then sources transportation services from the winning 3PLs by solving a corresponding winner determination problem (WDP). Specifically, the 4PL first releases a request for proposal (RFP) for a logistics network of lanes. Each bidder, i.e. every 3PL, then submits multiple bids. To guarantee that a 3PL could get a particular set of lanes with cost minimization, the bidding language utilized by 3PLs is assumed to have an XOR structure, that is, each 3PL that is allowed to submit a number of packages for lanes can win at most one package (Sandholm, 2002; Xu et al., 2015, 2017). After receiving all the bids from 3PLs, the 4PL solves the WDP so as to determine that the winning bids satisfy the clients' demand. It is worth noting that although XOR language is more expressive, it also requires each bidder to submit more packages (Scheffel et al., 2012).

To provide high quality of comprehensive supply chain solutions, a paramount concern of 4PL managers is sourcing transportation services from 3PLs that may involve disruptions, which are caused by natural disasters (floods, hurricanes, earthquakes, bad weather, ect.), intentional interdictions (terrorist attacks, labour strikes, ect.) or unintentional events (equipment breakdowns, industrial accidents, crew absence, ect.) (Choi et al., 2016; Huang et al., 2015; Snyder et al., 2016). There are several reasons why 4PL managers are becoming increasingly preoccupied with disruptions. First, these disruptions could cause not only serious operational consequences (loss of market shares, delivery delays, higher transportation costs, ect.), but also extended negative financial effects (abnormal stock returns, long recovering time, equity risk, ect.) (Peng et al., 2011; Mohammadi et al., 2016). For example, the Tōhoku earthquake and the following tsunami in Japan halted production in a broad range of the country's industries in 2011, because of plant damage, transportation blockage or power outages (Ang et al., 2017). Second, the logistics systems constructed under the assumption that 3PLs are immune to disruptions might be severely ruined if disruption occurs without countermeasures, which would have adverse impact on customer satisfaction, operation efficiency and revenue performance (Chung et al., 2015; Qin et al., 2013). Third, the prevalence of modern concepts such as outsourcing, lean manufacturing, quick response, and postponement would further result in the network capacity of 3PLs being more vulnerable to disruptions, because of reduced buffers that a 3PL could fall back on in the event of disruptions (Snyder et al., 2016). In this paper, we mainly focus on the accidental disruptions caused by unintentional events.

Noting that even minor disruptions can have significant impact on logistics systems (Cheng et al., 2018), various tools could be adopted for managing disruption risks. First, the redundancy or flexibility strategy enables the 4PL to redesign an entirely existing logistics network, allowing the 4PL to avoid or rectify weaknesses that may potentially cause disruptions (Klibi et al., 2010). However, changing 3PLs or reconfiguring the network could be costly, and thus may not be always reasonable. Second, the fortification strategy indicates investing in focal 3PLs to reduce the odds of a disruption, and thus can efficiently improve the reliability of logistics network. For example, strengthening a subset of the railway components could increase the functionality of the Chinese railway system in the presence of possible disasters (Yan et al., 2017). It is worth noting that this strategy is utilized in advance of a disruption, and thereby would incur a fortification cost regardless of whether a disruption occurs. Third, the outside option strategy implies that, in the face of a disruption, the 4PL can scramble to develop an alternate option by using other 3PLs not included in CRA. For example, when the surge demand on Single's Day threatened to delay the delivery of goods, Cainiao Logistics, founded by the Alibaba Group, could work together with China Railway High-speed (CRH) Express to create an alternate option[3]. Fourth, the non-performance penalty strategy levies penalty fees on a 3PL in the event that the 3PL fails to deliver on its promises. Yet, this strategy may severely cause customer dissatisfaction and bad reputation. Since the reservation strategy could improve the efficiency of logistics systems in logistics industry (Bai et al., 2017), in this paper, we assume that the 4PL would adopt a hybrid mitigation strategy which is a combination of fortification, reservation (expanding capacity for fortified 3PLs) and outside option strategies to handle disruptions.

This paper models a novel combinatorial WDP for TSP of the 4PL facing capacity constrained 3PLs with disruptions under limited protection investment budget. We aim to investigate how CRA can be integrated with disruption mitigation strategies to reach an optimal procurement strategy for the 4PL. Our purpose is to select focal 3PLs with possible capacity disruptions through CRA from the 4PL's point of view so as to satisfy clients' transportation demands in a logistics network. To minimize the total cost of the 4PL, the disruption mitigation strategy should be carefully constructed by making a trade-off between reasonable allocation of limited protection investment, reservation capacity in fortified 3PLs and the utilization of outside options. A two-stage stochastic mixed-integer winner determination model (TSMWDM), integrating a hybrid disruption mitigation strategy, is established. In the first stage, the 4PL minimizes the fortification cost and expected cost of stage 2 to determine the packages to be fortified. In the second stage, the 4PL minimizes the total cost of each scenario, including the procurement cost, holding cost of reservation capacity, fixed transaction cost of relationship management, and the outside option cost for failing to satisfy the requirements of clients via CRA, to determine the winning 3PLs.

Our work contributes to the reverse auction and logistics literature by integrating a hybrid disruption mitigation strategy with CRA to propose an optimal procurement strategy for the 4PL. To solve the deterministic equivalent reformulation of TSMWDM, a scenario-reduction-based approach is developed for solution method. Relaxing the original problem to utilize the CPLEX solver or developing an efficient dual decomposition and Lagrangian relaxation approach, we could obtain a lower bound of TSMWDM to evaluate the performance of the scenario reduction approach. Numerical results illustrate the effectiveness and applicability of the proposed model and method. We find that the hybrid disruption mitigation strategy is the best choice for the 4PL by comparing it with other known strategies, and would have a more significant influence on the cost minimization as the probability of disruption becomes higher. We also develop two separate extensions of TSMWDM to consider the settings of partially disrupted packages and no execution risk, and evaluate the expected cost of TSP for the 4PL under each extended model. We believe that our work could benefit the realization of a cost-effective logistics system under disruptions.

[3]http://www.chinadaily.com.cn/business/2016-11/12/content_27356494.htm

The rest of this paper is organized as follows. In Section 2, the related literature is briefly reviewed for this study. In Section 3, we mainly focus on the formulation of TSMWDM and the corresponding extensions. Section 4 introduces the scenario reduction approach to obtain representative scenarios for solution method. Section 5 is the evaluation of the method and the effect of critical parameters on the hybrid disruption mitigation strategy. We conclude this paper with some future extensions in Section 6.

2. Literature Review

In this paper, we study a combinatorial WDP under disruptions associated with potential 3PLs. The literature related to our work comes from two separate streams, that is, WDP and disruption mitigation strategies.

2.1. Winner determination

Due to the potential saving of approximately 3% to 15% of the procurement cost, using CRA for TSP has become a new trend (Hu et al., 2016; Zhang et al., 2014). Roughly, the investigation of CRA for TSP can be split into two streams. The first stream of the literature addressed the optimal bidding strategy from the bidders' point of view (Basu et al., 2015; Chang, 2009; Kuyzu et al., 2015; Lee et al., 2007; Song & Regan, 2005; Triki et al., 2014). These studies formulate bid generation and evaluation models to help bidders determine a set of valuable lanes to bid for by maximizing the revenue with optimization algorithms in CRA. For example, Chang (2009) developed a bidding advisor to help truckload determination of desirable bid packages using a column generation approach. Triki et al. (2014) considered a stochastic bid generation problem and developed a probabilistic optimization model to maximize the carrier's profit using two heuristic procedures. The second stream of the literature investigated WDP (Ma et al., 2010; Mansouri & Hassini, 2015; Remli & Rekik, 2012, 2013; Qian et al., 2017; Zhang et al., 2014, 2015). These studies attempted to allocate optimally the bundles of goods to bidders by maximizing the auctioneer's revenue. Noting that the WDP in its basic form is equivalent to the weighted set packing, which is an NP-complete combinatorial optimization problem (Rothkopf et al., 1998), this paper emphasizes the WDP model and the corresponding method.

A variety of WDP models have been developed for TSP to increase procurement efficiency, showing the growing interest and importance of CRA. Most of the models developed so far focused on deterministic WDP. For example, Caplice & Sheffi (2003) initially examined mathematical models for assigning lanes to specific carriers (winner determination) with or without package bids, and discussed the extension by including business side constraints. Sandholm et al. (2005) studied a general WDP to provide a sophisticated optimal search algorithm that comprises decomposition techniques, upper and lower bounds, heuristics and a host of structural observations. To solve large-scale WDP, a number of optimization algorithms were developed in the subsequent works, such as branch and cut (Escudero et al., 2009), memetic (Boughaci et al., 2009), weighted maximum clique heuristic (Wu & Hao, 2015), Lagrangian relaxation (Mansouri & Hassini, 2015), ant colony algorithm (Qian et al., 2017) and so on. Investigating more complex WDPs that integrate multi-attributes (Bichler & Kalagnanam, 2005; Buer & Kopfer, 2014; Huang et al., 2016) or behavior (Ray et al., 2011; Qian et al., 2018a,b, 2019) has become popular in the use of CRA for TSP in real-life applications.

One important factor not involved in the abovementioned research is uncertainty, which might have dire consequences and compromise the efficiency of a solution (Remli & Rekik, 2013). In practice, shippers' demands and carriers' capacities could be uncertain due to natural and man-made incidents as mentioned in Section 1. The development of WDP models under uncertainty is very recent field of research. Most of the WDP models developed so far have mainly focused on stochastic shipment volume to reduce the impact of uncertainties. To better formulate the problem, a two-stage stochastic winner determination framework was introduced, in which the first-stage decision is made before the realization of the uncertain demand, and the second-stage decision would be made to improve the utility once the value of uncertain parameters is observed. Following the framework, assuming that the realization of the random volume of shipments on each lane is at three levels, Ma et al. (2010) constructed a mathematical model with comprehensive business side constraints and showed the advantage of the proposed model by comparing it with a deterministic one. Similarly, Zhang et al. (2014) assumed that the uncertain demand followed a known distribution and developed a Monte Carlo approximation approach for solving the corresponding WDP. To reduce the impact of worst-case losses under shipment volume uncertainty, a two-stage robust winner determination model was also investigated (Remli & Rekik, 2013; Zhang et al., 2015).

To the best of our knowledge, most models available today investigate the winner determination problem under the scenario of shipment volume uncertainty. On a different line, our study arises from the real operational problems faced by a 4PL provider who needs to select 3PLs with possible accidental disruptions for satisfying clients' demands by solving the WDP. Compared with the existing studies, the novel stochastic WDP with a hybrid disruption mitigation strategy investigated in this paper is more comprehensive, and not only ensures the effectiveness of the hybrid mitigation strategy to satisfy clients' demand in the face of a disruption, but also determines other 3PLs not included in the auction after knowing the survived packages in a cost-optimal way. Indeed, our problem can be formulated as a risk-neutral expected-cost model in the two-stage stochastic winner determination framework. More specifically, the first-stage decision determines the fortified packages of 3PLs, and the second-stage determines the winning 3PLs, the reservation capacity of fortified packages, and the utilization of outside options once the values of disruption parameters are observed.

2.2. Disruption mitigation strategies

Due to the globalization of business operations, logistics systems are increasingly vulnerable to many sources of disruptions caused by natural disasters, accidental events or intentional attacks (Choi et al., 2016). Noting that the disruptions could have a dramatic impact on the logistics system, a number of studies underline the importance of developing disruption mitigation strategies to increase the reliability of the logistics system in a cost-effective way (Fattahi et al., 2017; Snediker et al., 2008; Torabi et al., 2015). Roughly, the research area of logistics disruption management can be divided into two separate streams. The first one concerned the development of reactive policies to hedge against negative impacts of different disruptions. This stream generally constructed disruption recovery models to adjust the structure of logistics networks, and was focused by many researchers (Li et al., 2015; Paul et al., 2017; Sawik, 2019; Unnikrishnan & Figliozzi, 2011). An recent review of the literature on this stream can be found in Ivanov et al. (2017). The second one focused on the development of proactive policies to protect against future disruptions. This stream generally formulated protection models to improve the reliability of logistics systems. Our paper would pay an emphasis on pertinent protection strategies which could be integrated with WDP models to minimize the disruption effects.

The development of redundancy policies for the logistics system is a topic that has received much attention recently. Most of the literature focused on building up flexibility to protect against disruptions and added redundancy to create an intrinsically reliable network through additional links connecting supply and demand. For example, aiming to design a robust supply chain network in the presence of random facility disruptions, Lim et al. (2010) developed a Lagrangian relaxation-based solution method for solving the corresponding mixed integer programming model. Similarly, Shen et al. (2011) constructed a two-stage stochastic programming model for the reliable facility location problem and developed several heuristics that can produce near-optimal solutions to solve the problem. Adding three redundancy policies, Kamalahmadi & Parast (2017) proposed a two-stage mixed integer programming model to mitigate the negative impacts of environmental disruptions on the supply chain network. In the subsequent works, variations on the basic formulation were investigated, such as forward-reverse logistics network (Hatefi & Jolai, 2014), uncertain corrected disruptions (Lu et al., 2015), health service network (Zarrinpoor et al., 2018), capacitated logistics network (Shishebori et al., 2017), proactive supply chain network (Ivanov et al., 2016), and so on. A recent review of the literature on this research area was given by Snyder et al. (2016).

Another class of literature focused on the fortification strategy to mitigate disruptions. When a logistics network is under the threat of disruption, it is crucial to fortify the most important facilities. The initial work to model the fortification decision was by Church & Scaparra (2007). It constructed an integer-linear programming model to optimally assign the fortification resources to the most critical facilities by minimizing the maximum possible damages. After that, various extensions of the basic models were studied, such as the shortest-path networks (Cappanera et al., 2011), capacitated supply chain network (Azad et al., 2013), hierarchical facility location (Aliakbarian et al., 2015), and hub-and-spoke networks (Ramamoorthy et al., 2018). The above fortification models developed could be classed as multi-level defender-attacks models in which the impact of worst-case losses was reduced as disruption occurs. In addition, other strategies could be utilized to hedge against the disruption risks. For example, strategically-reserved emergency capacity might be a straightforward way to add redundancy to protect against disruption (Bai et al., 2017; Ni et al., 2018). When a firm is subject to disruptions, it can also resort to its outside partners to improve the reliability (Ma et al., 2010). Most recently, adopting a combination of the aforementioned strategies to protect against disruption has become increasingly popular. For example, Qin et al. (2013) developed a combination of fortification and reservation strategies for the existing logistics system under accidental disruptions. However, these strategies were purely discussed in the formulation of the logistics and supply chain network, and cannot offer decision support for TSP using reverse auctions with disruptions in terms of 3PLs.

To address the gap in the literature, our study focuses on a hybrid mitigation strategy that provides a comprehensive measure including the fortification, reservation, and outside option schemes to reduce the impact of disruptions for 4PL under a novel two-stage stochastic winner determination framework. This paper serves to help the 4PL make better decisions of selecting 3PLs with disruptions to fulfill the demands of clients via CRAs by providing a mathematical model that integrates the hybrid mitigation strategy into the winner determination process and using the proposed model to generate insights for the 4PL to better manage 3PLs in the presence of disruptions. The contribution of this paper is therefore to demonstrate how the hybrid mitigation strategy can be integrated with CRAs to obtain an optimal procurement strategy for the 4PL when facing 3PLs with disruptions. The analysis verified by numerical experiments shows that the hybrid mitigation strategy is dominant over others and could be a useful tool for the 4PL to deal with disruptions in the use of CRAs for TSP.

3. Problem description, notations and modelling

To lower the cost and improve the efficiency of transportation service procurement (TSP) for clients, a combinatorial reverse auction (CRA) is frequently adopted by a 4PL (auctioneer) to solicit bids from a group of 3PLs (bidders). This paper studies a winner determination problem (WDP) of CRA from the 4PL's point of view. Most of existing WDP is carefully modeled as a deterministic mixed-integer program assuming fixed capabilities of 3PLs at the auction phase. However, in practice, accidental disruptions caused by unintentional events, such as vehicle breakdowns, driver discontinuities and accidental fires, can lead to capacity disruptions of 3PLs after the auction, which would have substantial impact on the previous decision of 4PL. Obviously, a deterministic winner determination model with an estimate of 3PL disruptions may not provide adaptive solutions to achieve procurement efficiency for the 4PL. Hence, the main focus of this paper is to investigate how risk mitigation strategies can be integrated with the WDP decisions of the existing logistics system to minimize the total cost of protection, reservation, outside option and expected procurement for the 4PL simultaneously. In the following discussion, we would first investigate the scenario in which the transportation capacity of a package for the 3PL could be totally disrupted, and defer the research problem in which the capacity of a package for the 3PL could be partially disrupted as an extension.

Let I be the set of lanes that the 4PL would serve. Each lane $i \in I$ has a specific demand d_i. Let J denote the set of 3PLs. Each 3PL $j \in J$ submits XOR bids K_j that each bidder although can submit any number of indivisible packages will win at most one package. The maximum capacity and bid price for each unit submitted by 3PL $j \in J$ on lane $i \in I$ for package $k \in K_j$ is denoted by US_{ijk} and b_{ijk}, respectively. A 3PL cannot be assigned more demand than its current capacity. The set of disruption scenarios denoted by S is finite. If package $k \in K_j$ of 3PL $j \in J$ is hit by a disruption scenario $w \in S$, then the package is completely unavailable throughout the recovery time. For convenience, we assume that the disruption scenarios are independent under the setting of capacity disruption (Qin et al., 2013). In other words, we consider that the disruption hits the package of each 3PL's capacity independently, which could generally happen in practical applications. For example, each package is associated with a set of vehicles that would serve the same lanes in that package at the same time. If a disruption occurs, the set of vehicles might be totally destroyed or have a breakdown such that they cannot serve the lanes any more. Other accidental events, such as traffic accidents and fires, may also cause independent disruptions across potential 3PLs (Lam & Su, 2015).

Let D denote the total number of situations that would induce possible disruptions, and $\mathbf{s} = (s_1, \ldots, s_D)^T$ denote the probability vector of situations that would induce possible disruptions, where s_d is a possible disruption induced by the d-th situation. Given L_D denoting the set of probably disrupted packages, noting that each package in L_D only have two states, i.e., disruption or non-disruption, we have $|S| = 2^{|L_D|}$. For example, given $L_D = \{1, 2\}$, we have $S = \{(0, 0), (0, 1), (1, 0), (1, 1)\}$, where the element $(1, 0)$ means package 1 is disrupted and package 2 is normal. With a slight abuse of notations, let $\hat{r}_k$ denote the disruption probability of the k-th package which belongs to the set L_D, $k \in L_D$. Given s_d^k being the disruption probability induced by the d-th situation for the k-th package, $k \in L_D$, $d = 1, \ldots, D$, following the literature (Snyder & Daskin, 2007), we have $\hat{r}_k = 1 - \prod_{d=1}^{D}(1 - s_d^k)$, where the value of s_d^k could be estimated by historical data or the forecast of experts. In this case, the probability of the disruption scenario w could be denoted by $r_w = \prod_{k \in L_{D_s}} \hat{r}_k \prod_{k \in \{L_D \setminus L_{D_s}\}}(1 - \hat{r}_k)$, where L_{D_s} denotes the set of disrupted packages under scenario w. The parameter q_{jkw} is introduced to indicate whether the package k of 3PL j is hit in scenario w. If the package k of 3PL j is disrupted, then q_{jkw} equals to 1 and otherwise 0.

Since 3PLs are vulnerable to capacity disruptions, to improve the service level, 4PL has to take protective measures to prevent these disruptions for focal 3PLs. Noting that redesigning the capacity of the 3PL would be prohibitively costly, we propose to apply the hybrid mitigation strategy including protection, reservation and outside option measures to deal with the disruption risks in advance. To be specific, the 4PL would provide a maximum investment $C_{\max}$ in fortifying key packages of 3PLs. The protection cost of fortifying 3PL $j \in J$ in terms of package $k \in K_j$ denoted by c_{jk} would depend on the capacity of 3PL j and the size of package k. Following the literature (Qin et al., 2013), we assume that the fortified packages could maintain the normal capacity of 3PLs even though disruption hits them. In addition, for the fortified package, the reservation capacity could be pre-positioned to counteract the adverse impact of disruptions. For example, the 4PL could invest in the backup capacity of 3PLs and reserve the capacity to hedge against disruptions. The unit holding cost of the reservation capacity and the maximum extended capacity of 3PL j for package k on lane i are denoted by h_{ijk} and LS_{ijk}, respectively. Without loss of generality, we assume that the extended capacity of the fortified package k for 3PL j on lane i is no more than the original maximum capacity US_{ijk}, and the unit holding cost h_{ijk} is higher than the bid price so as to reduce the total reservation capacity as much as possible. Note that if the volume of shipments is assigned to a winner, then a fixed transaction cost for relationship management of 3PL j on package k denoted by v_{jk} occurs. If the assigned volume does not meet the specified requirement of clients after disruptions, a costly outside option denoted by e_i would be adopted by the 4PL to fulfill the unsatisfied demand. To maintain the appropriate size of the 3PLs, the 4PL would like to have no more than or no less than a certain number of winning 3PLs, which could be denoted by $N_{\max}$ and $N_{\min}$, respectively. Based on these conditions, the 4PL can determine which packages of 3PLs should be fortified so as to counteract the adverse effect of disruptions, where would reservation capacity be pro-positioned, and what kind of outside option could be adopted if the winning 3PLs cannot fulfill the realized demand after disruptions.

The notations of the model are introduced below:

Parameters	
I	set of lanes
J	set of 3PLs
K_j	set of packages submitted by 3PL j
S	set of possible disruptions scenarios
d_i	demand of shipment volume on lane i
$C_{\max}$	maximum budget of protection investment
$N_{\min}$	minimum number of winning 3PLs of CRA specified by 4PL
$N_{\max}$	maximum number of winning 3PLs of CRA specified by 4PL, $N_{\max} \geq N_{\min}$
LS_{ijk}	maximum extended shipment volume on lane i in package k that can be shipped by 3PL j if its package k is fortified
US_{ijk}	maximum shipment volume on lane i in package k that can be shipped by 3PL j if he wins package k, $US_{ijk} \geq LS_{ijk}$
e_i	outside option cost for shipping 1 unit of freight on lane i by other 3PLs who are not invited to CRA
b_{ijk}	bid price of shipping 1 unit of demand on lane i quoted by 3PL j on package k
c_{jk}	protection cost of 3PL j on package k
h_{ijk}	unit cost of reservation shipment volume pre-positioned on lane i by 3PL j on package k
q_{jkw}	0-1 indicated parameter, $q_{jkw} = 1$ indicates that 3PL j is hit on package k in scenario w
r_w	probability of a disruption scenario, $w \in S$
v_{jk}	fixed transaction cost between the 4PL and 3PL j on package k
Decision variables	
x_{jk}	1 if 3PL j's package k is fortified and 0 otherwise
z_{ijk}	shipment volume reserves on lane i if 3PL j's package k is fortified
y_{ijkw}	shipment volume assigned to 3PL j on lane i in package k under scenario w
p_{jk}	1 if 3PL j wins the package k and 0 otherwise
φ_{iw}	shipment volume on lane i under scenario w that is assigned to other 3PLs who are not invited to participate in CRA

The WDP integrating disruption mitigation strategies can be formulated in a two-stage stochastic mixed-integer programming model as shown below.

$$\min \quad \sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jk} + \mathrm{E}[f(x, w)] \tag{1}$$

s.t.

$$\sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jk} \leq C_{\max} \tag{2}$$

$$x_{jk} \in \{0, 1\}, \quad j \in J,\ k \in K_j \tag{3}$$

$$\text{where } f(x, w) = \sum_{i \in I} \left(\sum_{j \in J} \sum_{k \in K_j} (b_{ijk} y_{ijkw} + h_{ijk} z_{ijk} + v_{jk} p_{jk}) + e_i \varphi_{iw} \right) \tag{4}$$

s.t.

$$\sum_{j \in J} \sum_{k \in K_j} y_{ijkw} + \varphi_{iw} = d_i, \quad i \in I,\ w \in S \tag{5}$$

$$q_{jkw} x_{jk} US_{ijk} + (1 - q_{jkw}) US_{ijk} \geq y_{ijkw} - z_{ijk}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S \tag{6}$$

$$x_{jk} LS_{ijk} \geq z_{ijk}, \quad i \in I,\ j \in J,\ k \in K_j \tag{7}$$

$$M p_{jk} \geq y_{ijkw}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S \tag{8}$$

$$\sum_{k \in K_j} p_{jk} \leq 1, \quad j \in J \tag{9}$$

$$\sum_{j \in J} \sum_{k \in K_j} p_{jk} \leq N_{\max} \tag{10}$$

$$\sum_{j \in J} \sum_{k \in K_j} p_{jk} \geq N_{\min} \tag{11}$$

$$p_{jk} \in \{0, 1\}, \quad j \in J,\ k \in K_j \tag{12}$$

$$y_{ijkw},\ z_{ijk},\ \varphi_{iw} \geq 0, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S \tag{13}$$

In the following discussion, we refer to the above formulation as a two-stage stochastic mixed-integer winner determination model (TSMWDM). Eq. (1) is the objective function of the first-stage problem that minimizes the fortification cost of packages for 3PLs and the expected cost of stage 2. Eq. (2) guarantees that the fortification investment cannot exceed the maximum budget. Eq. (3) is a constraint that indicates the integrality requirement of the fortification variables. Eq. (4) is the objective function of the second-stage problem that minimizes the total cost of the 4PL under each scenario. Specifically, the total cost includes the procurement cost, holding cost of reservation capacity, fixed transaction cost of relationship management, and outside option cost for failing to satisfy the requirements by 3PLs via the auction. Eq. (5) requires that the shipping demand on each lane is satisfied either by the winning 3PLs in the auction or the outside 3PLs who are not invited to the auction but are still able to provide transportation services. Eq. (6) ensures that the shipment volume assigned to each 3PL is not more than the maximum capacity depending on whether the package is fortified or not interdicted. Eq. (7) requires that the reservation capacity of the fortified package for each 3PL on the corresponding lane can be extended up to the maximum value LS_{ijk}. Eq. (8) ensures that the package of a 3PL would be selected if the assigned shipment volume is greater than zero. Note that M is a sufficiently large number. In this model, the smallest value for M could be computed by $\max_{i \in I,\ j \in J,\ k \in K_j} \{US_{ijk}\}$. Eq. (9) represents the

XOR bidding language that at most one package of each 3PL could be selected. Eqs. (10) and (11) ensure that the number of 3PLs simply has to be between a certain pre-specified interval. Eqs. (12) and (13) are integrality constraints and nonnegativity constraints of decision variables, respectively.

Obviously, the deterministic equivalent reformulation of TSMWDM is a mixed-integer program. Since the decision variables and constraints of the research problem would tremendously increase as the set of scenarios S becomes large, the corresponding model becomes too complicated to be solved by commercial solvers like CPLEX solver directly. In the next section, an effective scenario reduction approach is developed for solution method.

3.1. Extensions

In this subsection, we would give two extended models by relaxing some assumptions made in TSMWDM. The first subsubsection presents an extension that allows the partially disrupted package instead of the totally disrupted one. In this case, given the capacity associated with some lane in a package being hit by a disruption, the 3PL can still provide transportation services for other lanes in that package. In addition, the 4PL would fortify the transportation capacity associated with lanes that might be disrupted instead of fortifying the probably disrupted packages, and the fortified capacity of lanes could still have a chance to be destroyed under disruptions. The second extension in the second subsubsection assumes that the 4PL faces 3PLs with a risk of miss/no execution of contracts. In this case, since the fortification strategy cannot function any more, following the literature (Gong et al., 2018; Kutanoglu & Lohiya, 2008), we would integrate the penalty policy and the outside options with the CRA to propose an optimal procurement strategy for the 4PL.

3.1.1. Partially disrupted packages

In this subsubsection, for practical applications, we discuss a variation of our basic models to consider the case of partially disrupted packages, that is, the capacity associated with lanes in a package might be disrupted. If a disruption $w \in S$ hits the capacity of lane $i \in I$ for 3PL $j \in J$, then the capacity of lane i is completely unavailable for 3PL j in any package $k \in K_j$ throughout the recovery time, but the capacity of any other lane $\hat{i} \in I \backslash \{i\}$ can still function normally for $\hat{i} \neq i$ in the package. Since the capacity of lanes might be vulnerable to disruptions, to ensure the service level, the 4PL could provide a maximum investment $C_{\max}$ in fortifying the capacity of key lanes for 3PLs to prevent these disruptions. Without loss of generality, we assume that the capacity of fortified lanes could function normally with a probability. Let $\theta \in \Theta$ denote the state that the fortified capacity of lanes could survive or be destroyed under a disruption, where $\Theta = \{1, 2\}$. Obviously, the state can be characterized by a discrete random variable that follows a Bernoulli distribution. We assume that the random variable takes the value $\mu_1 = 1$ with probability ρ_1 and the value $\mu_2 = 0$ with probability ρ_2 such that $\rho_1 + \rho_2 = 1$. In the meanwhile, the fortified capacity of lanes would have a chance of μ_θ to be reserved for the purpose of counteracting the adverse impact of possible disruptions, $\theta \in \Theta$. More details about the fortification and reservation strategies applied to the capacity of lanes of logistics systems can be found in Yan et al. (2017) and Bai et al. (2017).

With a slight abuse of notation, given r_{i_j} denoting the disruption probability of the capacity associated with lane $i \in I$ for 3PL j, the probability of a scenario w can be rewritten as $r_w = \prod_{i_j \in D_s} r_{i_j} \prod_{i_j \in \{D \backslash D_s\}} (1-$

r_{i_j}), where D_s is the set of probably disrupted capacity of lanes associated with potential 3PLs. Other notations follow similarly as our basic model. The winner determination problem integrated with capacity disruption of lanes for the logistics system can be constructed as a two-stage stochastic mixed-integer programming model as shown below.

$$\min \quad \sum_{i\in I}\sum_{j\in J} c_{ij}x_{ij} + \mathrm{E}[f(x,w)] \tag{14}$$

s.t.

$$\sum_{i\in I}\sum_{j\in J} c_{ij}x_{ij} \le C_{\max} \tag{15}$$

$$x_{ij} \in \{0,1\}, \quad i \in I,\ j \in J \tag{16}$$

$$\text{where } f(x,w) = \sum_{\theta\in\Theta} \rho_\theta \left[\sum_{i\in I} \left(\sum_{j\in J}\sum_{k\in K_j} (b_{ijk}y_{ijkw\theta} + h_{ijk}z_{ijk} + v_{jk}p_{jk}) + e_i\varphi_{iw\theta} \right) \right] \tag{17}$$

s.t.

$$\sum_{j\in J}\sum_{k\in K_j} y_{ijkw\theta} + \varphi_{iw\theta} = d_i, \quad i \in I,\ w \in S,\ \theta \in \Theta \tag{18}$$

$$q_{ijkw}x_{ij}\mu_\theta(US_{ijk} + z_{ijk}) + (1 - q_{ijkw})US_{ijk} \ge y_{ijkw}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S,\ \theta \in \Theta \tag{19}$$

$$x_{ij}LS_{ijk} \ge z_{ijk}, \quad i \in I,\ j \in J,\ k \in K_j \tag{20}$$

$$Mp_{jk} \ge y_{ijkw\theta}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S,\ \theta \in \Theta \tag{21}$$

$$\sum_{k\in K_j} p_{jk} \le 1, \quad j \in J \tag{22}$$

$$\sum_{j\in J}\sum_{k\in K_j} p_{jk} \le N_{\max} \tag{23}$$

$$\sum_{j\in J}\sum_{k\in K_j} p_{jk} \ge N_{\min} \tag{24}$$

$$p_{jk} \in \{0,1\}, \quad j \in J,\ k \in K_j \tag{25}$$

$$y_{ijkw\theta},\ z_{ijk},\ \varphi_{iw\theta} \ge 0, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S,\ \theta \in \Theta \tag{26}$$

Obviously, the model characterized by Eqs. (14)-(26) has the same structure and similar interpretations as that of Eqs. (1)-(13). In stage 1, the fortification cost of probably disrupted capacity of lanes and the excepted cost of stage 2 would be minimized. In stage 2, we minimize the total expected cost associated with the situation whether the fortified capacity of lanes would be available or not under each scenario. Similarly, the total expected cost includes the procurement cost, holding cost of reservation capacity, fixed transaction cost of relationship management, and outside option cost for failing to satisfy the requirements by 3PLs via the auction.

3.1.2. No execution risk of 3PLs

In practical applications, it is important for the 4PL to manage 3PLs for fulfilling clients' demands to achieve customer satisfaction under disruptions. If clients are not served, then the no execution risk occurs, and the failure to accomplish the clients' demand would impose consequences on the 4PL, such as loss of money and bad reputations (Kozhan & Tham, 2012). To avoid potential losses, a penalty cost $\hat{h}_{jk}$ is charged to each no execution 3PL, and unsatisfied demand would be fulfilled by using the outside options, $j \in J, k \in K_j$. The winner determination problem associated with the no execution risk of potential 3PLs could be formulated as a two-stage stochastic mixed-integer programming model, where the winning 3PLs would be determined in stage 1, and the allocation of the shipment volume would be determined in stage 2. The details of the model are given below.

$$\min \quad \sum_{j\in J}\sum_{k\in K_j} v_{jk}p_{jk} + \mathrm{E}[f(p,w)] \tag{27}$$

s.t.

$$\sum_{k\in K_j} p_{jk} \le 1, \quad j \in J \tag{28}$$

$$\sum_{j\in J}\sum_{k\in K_j} p_{jk} \le N_{\max} \tag{29}$$

$$\sum_{j\in J}\sum_{k\in K_j} p_{jk} \ge N_{\min} \tag{30}$$

$$p_{jk} \in \{0,1\}, \quad j \in J,\ k \in K_j \tag{31}$$

$$\text{where } f(p,w) = \sum_{i\in I}\left(\sum_{j\in J}\sum_{k\in K_j} b_{ijk}y_{ijkw} + e_i\varphi_{iw}\right) - \sum_{j\in J}\sum_{k\in K_j} q_{jkw}p_{jk}\hat{h}_{jk} \tag{32}$$

s.t.

$$\sum_{j\in J}\sum_{k\in K_j} y_{ijkw} + \varphi_{iw} = d_i, \quad i \in I,\ w \in S \tag{33}$$

$$p_{jk}(1-q_{jkw})US_{ijk} \ge y_{ijkw}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S \tag{34}$$

$$y_{ijkw},\ \varphi_{iw} \ge 0, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S \tag{35}$$

Obviously, we see that the structure of the winner determination model associated with the no execution risk is similar to our basic model. Eq. (27) is the objective function of the first-stage problem that minimizes the transaction cost and the expected cost of stage 2 simultaneously. Eq. (32) is the objective function of the second-stage problem that minimizes the total cost of the 4PL under each scenario, including the procurement cost, outside option cost for failing to satisfy the requirements by 3PLs via the auction and the penalty cost derived from 3PLs of no execution behavior. Eq. (34) ensures that the maximum capacity of each 3PL can not be exceeded. The interpretation of other equations are the same to our basic model.

4. Solution methodology

Noting that solving the winner determination problem with disruptions expressed by TSMWDM is difficult, since a huge number of variables and constraints would be involved as the number of scenarios increases, the scenario reduction approach is developed for a solution method. The main idea of the scenario reduction approach is to decrease the difference between the optimal objective value of the original problem with full scenarios and the optimal objective value of the reduced problem by selecting a subset from the original set of scenarios. In this case, the large set of full scenarios can be well approximated by a small set of reduced scenarios that could yield a good solution close to the optimal one of the original problem (Karuppiah et al., 2010).

Given $L = |L_D|$ denoting the number of probably disrupted packages and $\gamma = \{\gamma_k\}_{k=1,\ldots,L}$ being the vector of uncertain parameters associated with the case whether package k is disrupted or not, $k \in L_D$, each γ_k could be assumed to take on a finite set of values given by $\{\gamma_k^{l_k}\}_{l_k=1,2}$. Noting that 0 and 1 could be used to indicate whether package k is immune to a disruption or not, that is $\gamma_k^{l_k} \in \{0,1\}$ for $k \in L_D$ and $l_k = 1,2$, we see that the probability associated with the uncertain parameter γ_k taking on $\gamma_k^{l_k}$ is $r_k^{l_k}$. Correspondingly, the probability associated with a scenario w in the original set of scenarios is given by $r_{l_1,l_2,\ldots,l_L} = \prod_{k=1}^{L} r_k^{l_k}$. Hence, the relaxation formulation to determine the minimum number of scenarios is introduced below (Karuppiah et al., 2010; Sadghiani et al., 2015).

$$\min \quad f = \sum_{l_1=1}^{2}\sum_{l_2=1}^{2}\cdots\sum_{l_L=1}^{2}[(1 - r_1^{l_1} r_2^{l_2}\cdots r_L^{l_L})\cdot \hat{r}_{l_1,l_2,\ldots,l_L}] \tag{36}$$

s.t.

$$\sum_{l_2=1}^{2}\sum_{l_3=1}^{2}\cdots\sum_{l_L=1}^{2}\hat{r}_{l_1,l_2,\ldots,l_L} = r_1^{l_1}, \quad l_1 = 1,2 \tag{37}$$

$$\sum_{l_1=1}^{2}\sum_{l_3=1}^{2}\cdots\sum_{l_L=1}^{2}\hat{r}_{l_1,l_2,\ldots,l_L} = r_2^{l_2}, \quad l_2 = 1,2 \tag{38}$$

$$\vdots$$

$$\sum_{l_1=1}^{2}\sum_{l_2=1}^{2}\cdots\sum_{l_{L-1}=1}^{2}\hat{r}_{l_1,l_2,\ldots,l_L} = r_L^{l_L}, \quad l_L = 1,2 \tag{39}$$

$$\sum_{l_1=1}^{2}\sum_{l_2=1}^{2}\cdots\sum_{l_L=1}^{2}\hat{r}_{l_1,l_2,\ldots,l_L} = 1 \tag{40}$$

$$0 \le \hat{r}_{l_1,l_2,\ldots,l_L} \le 1, \quad \forall l_1, l_2, \ldots, l_L \tag{41}$$

where $\hat{r}_{l_1,l_2,\ldots,l_L}$ denotes the new probability assigned to a scenario. Using the CPLEX solver, we can find the most effective scenarios for TSMWDM. After that, the deterministic equivalent reformulation of TSMWDM expressed below can be solved by the CPLEX solver.

$$\min \sum_{j\in J}\sum_{k\in K_j} c_{jk}x_{jk} + \sum_{w\in S} r_w \cdot \left[\sum_{i\in I}\left(\sum_{j\in J}\sum_{k\in K_j}(b_{ijk}y_{ijkw} + h_{ijk}z_{ijk} + v_{jk}p_{jk}) + e_i\varphi_{iw}\right)\right] \tag{42}$$
$$\text{s.t.} \qquad \text{constraints} \;\; (2)\sim(3), (5)\sim(13)$$

To show the effectiveness of the scenario reduction approach, we give the theoretical error estimates by comparing it with other methods (i.e., using the full scenario approach to derive the optimal solution, relaxing the original problem to obtain a lower bound or adopting an efficient dual decomposition and Lagrangian relaxation approach to derive a lower bound) as shown below.

Let $(\mathbf{x}^T, \mathbf{p}^T, \mathbf{z}^T)^T$ and $f(\mathbf{x}, \mathbf{p}, \mathbf{z})$ denote the optimal solution and the corresponding optimal objective function value derived from the scenario reduction approach, respectively. Obviously, $(\mathbf{x}^T, \mathbf{p}^T, \mathbf{z}^T)^T$ is a feasible solution of TSMWDM. Hence $f(\mathbf{x}, \mathbf{p}, \mathbf{z})$ provides an upper bound of TSMWDM. Let $f^*(\mathbf{x}^*, \mathbf{p}^*, \mathbf{z}^*)$

denote the optimal objective function value of TSMWDM. The error of the optimal solution associated with the research problem under reduced scenarios denoted by ϵ could be calculated by $\epsilon = f(\mathbf{x}, \mathbf{p}, \mathbf{z}) - f^*(\mathbf{x}^*, \mathbf{p}^*, \mathbf{z}^*)$, where $f^*(\mathbf{x}^*, \mathbf{p}^*, \mathbf{z}^*)$ can be computed by the summation of the weighted optimal values of solving each scenario separately or approximated by taking a subset of scenarios with larger probabilities (Karuppiah et al., 2010). In this case, ϵ could be used to evaluate the effectiveness of the scenario reduction approach for the purpose of theoretical analysis or practical applications.

In general, when the number of disruption scenarios is sufficiently large, it could be impossible to obtain $f^*(\mathbf{x}^*, \mathbf{p}^*, \mathbf{z}^*)$ by using the CPLEX solver directly. In this case, evaluating the performance of the scenario reduction approach becomes extremely difficult, since the error ϵ cannot be derived. Next, we would provide two methods to derive the lower bound of TSMWDM, since the gap between the upper bound and lower bound could be adopted to evaluate the performance of the scenario reduction approach (Meng et al., 2012, 2015).

Relaxing Eq. (6) by setting $q_{jkw} = 0$, we have a simple version of TSMWDM denoted by (SP) in which the transportation capacity of each 3PL would never be disrupted under diverse scenarios, that is,

$$
\begin{aligned}
\text{(SP)} \qquad & \min \sum_{j\in J}\sum_{k\in K_j} c_{jk}x_{jk} + \sum_{w\in S} r_w \cdot \left[\sum_{i\in I}\left(\sum_{j\in J}\sum_{k\in K_j}(b_{ijk}y_{ijkw} + h_{ijk}z_{ijk} + v_{jk}p_{jk}) + e_i\varphi_{iw}\right)\right] \\
& \text{s.t.} \qquad \text{constraints } \ (2) \sim (3), (5), (7) \sim (13) \\
& \qquad\qquad US_{ijk} \geq y_{ijkw} - z_{ijk}, \quad i \in I,\ j \in J,\ k \in K_j,\ w \in S
\end{aligned} \tag{43}
$$

Solving (SP), we derive the following proposition.

PROPOSITION 1. *Given $(\hat{\mathbf{x}}^T, \hat{\mathbf{p}}^T, \hat{\mathbf{z}}^T)^T$ and $\hat{f}(\hat{\mathbf{x}}, \hat{\mathbf{p}}, \hat{\mathbf{z}})$ denoting the optimal solution and the corresponding optimal objective function value of (SP), $\hat{f}(\hat{\mathbf{x}}, \hat{\mathbf{p}}, \hat{\mathbf{z}})$ produces a lower bound of TSMWDM.*

Proof. Noting that (SP) is indeed a certain problem irrelevant with the disruption scenarios, the optimal solution of TSMWDM is always a feasible solution of (SP). Hence, we have $f^*(\mathbf{x}^*, \mathbf{p}^*, \mathbf{z}^*) \geq \hat{f}(\hat{\mathbf{x}}, \hat{\mathbf{p}}, \hat{\mathbf{z}})$. Solving (SP) to derive $(\hat{\mathbf{x}}^T, \hat{\mathbf{p}}^T, \hat{\mathbf{z}}^T)^T$ by using the CPLEX solver directly, we could derive a lower bound of TSMWDM, i.e., $\hat{f}(\hat{\mathbf{x}}, \hat{\mathbf{p}}, \hat{\mathbf{z}})$. □

Calculating $\hat{\epsilon} = f(\mathbf{x}, \mathbf{p}, \mathbf{z}) - \hat{f}(\hat{\mathbf{x}}, \hat{\mathbf{p}}, \hat{\mathbf{z}})$, we could evaluate the performance of the scenario reduction approach. If $\hat{\epsilon}$ does not provide a good estimation, then we could develop another approach to find the lower bound of TSMWDM as presented below.

Noting that TSMWDM is computationally intractable for sufficiently large number of disruption scenarios, an efficient dual decomposition and Lagrangian relaxation approach proposed by CarøE & Schultz (1999) is employed to find a lower bound for TSMWDM. Since the deterministic formula of TSMWDM can be divided into $|S|$ subproblems matching $|S|$ disruptions, the decision variables $(\mathbf{x}^T, \mathbf{p}^T, \mathbf{z}^T)^T$ shall be rewritten $|S|$ times to ensure the equivalence of the decision variables across all the subproblems.

Correspondingly, we have the following decomposition formula of TSMWDM denoted by (DP).

$$\text{(DP)} \quad \min \sum_{w \in S} r_w \cdot \left[\sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jkw} + \sum_{i \in I} \left(\sum_{j \in J} \sum_{k \in K_j} (b_{ijk} y_{ijkw} + h_{ijk} z_{ijkw} + v_{jk} p_{jkw}) + e_i \varphi_{iw} \right) \right] \tag{44}$$

$$\text{s.t.} \quad \text{constraints } (2) \sim (3), (5) \sim (13)$$

$$(\mathbf{x}_w^T, \mathbf{p}_w^T, \mathbf{z}_w^T)^T = (\mathbf{x}_{w+1}^T, \mathbf{p}_{w+1}^T, \mathbf{z}_{w+1}^T)^T, \quad w = 1, 2, \cdots, |S| - 1 \tag{45}$$

$$(\mathbf{x}_{|S|}^T, \mathbf{p}_{|S|}^T, \mathbf{z}_{|S|}^T)^T = (\mathbf{x}_1^T, \mathbf{p}_1^T, \mathbf{z}_1^T)^T \tag{46}$$

Given $|X|$, $|P|$, $|Z|$ denoting the number of elements in matrix $\mathbf{x}$, $\mathbf{p}$, $\mathbf{z}$, respectively, using the matrix notation, Eqs. (45) and (46) can be reformulated as $\sum_{w \in S} \mathbf{H}_w (\mathbf{x}_w^T, \mathbf{p}_w^T, \mathbf{z}_w^T)^T = 0$, where $\mathbf{H}_w$ is a matrix with $|S| \times (|X| + |P| + |Z|)$ rows and $|X| + |P| + |Z|$ columns, $w \in S$. In specific, $\mathbf{H}_1 = (-\mathbf{I}, \mathbf{I}, \mathbf{0}, \cdots, \mathbf{0})^T$, $\mathbf{H}_2 = (\mathbf{0}, -\mathbf{I}, \mathbf{I}, \cdots, \mathbf{0})^T$, $\cdots$, $\mathbf{H}_{|S|-1} = (\mathbf{0}, \mathbf{0}, \cdots, -\mathbf{I}, \mathbf{I})^T$ and $\mathbf{H}_{|S|} = (\mathbf{I}, \mathbf{0}, \cdots, \mathbf{0}, -\mathbf{I})^T$, where $\mathbf{I}$ and $\mathbf{0}$ are identity and zero matrices with $(|X| + |P| + |Z|)^2$ elements, respectively. Given $\boldsymbol{\lambda}$ denoting a vector of Lagrangian multiplier with $|S| \times (|X| + |P| + |Z|)$ elements, the Lagrangian relaxation problem of (DP) denoted by (LR) is

$$\begin{aligned} LR(\boldsymbol{\lambda}) \;=\; \min \; & \sum_{w \in S} r_w \cdot \left[\sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jkw} + \sum_{i \in I} \left(\sum_{j \in J} \sum_{k \in K_j} (b_{ijk} y_{ijkw} + h_{ijk} z_{ijkw} + v_{jk} p_{jkw}) + e_i \varphi_{iw} \right) \right] \\ & + \boldsymbol{\lambda}^T \sum\nolimits_{w \in S} \mathbf{H}_w (\mathbf{x}_w^T, \mathbf{p}_w^T, \mathbf{z}_w^T)^T \end{aligned} \tag{47}$$

$$\text{s.t.} \quad \text{constraints } (2) \sim (3), (5) \sim (13)$$

Since (LR) is separable in terms of each scenario $w \in S$, the subproblem of (LR) that is associated with scenario w denoted by (SLR) is expressed below.

$$\begin{aligned} LR_w(\boldsymbol{\lambda}) \;=\; \min \; & r_w \cdot \left[\sum_{j \in J} \sum_{k \in K_j} c_{jk} x_{jkw} + \sum_{i \in I} \left(\sum_{j \in J} \sum_{k \in K_j} (b_{ijk} y_{ijkw} + h_{ijk} z_{ijkw} + v_{jk} p_{jkw}) + e_i \varphi_{iw} \right) \right] \\ & + \boldsymbol{\lambda}^T \mathbf{H}_w (\mathbf{x}_w^T, \mathbf{p}_w^T, \mathbf{z}_w^T)^T \end{aligned} \tag{48}$$

$$\text{s.t.} \quad \text{constraints } (2) \sim (3), (5) \sim (13)$$

It is worth noting that (SLR) is a small-scale integer linear programming model which can be solved by the CPLEX solver directly. Then, we can derive another lower bound of TSMWDM by solving the associate Lagrangian dual problem denoted by (LD) as follows.

$$LD(\boldsymbol{\lambda}) = \max_{\boldsymbol{\lambda}} \; LR(\boldsymbol{\lambda}) \tag{49}$$

Since (LD) is a concave maximum problem with a non-differentiable objective function, it can be solved by the subgradient method. Let $\sum_{w \in S} \mathbf{H}_w ((\mathbf{x}_w^*)^T, (\mathbf{p}_w^*)^T, (\mathbf{z}_w^*)^T)^T$ denote a subgradient of (LD), where $((\mathbf{x}_w^*)^T, (\mathbf{p}_w^*)^T, (\mathbf{z}_w^*)^T)^T$ is a vector that denotes the optimal solution of the w-th subproblem of (LD). The details of the subgradient method for deriving a lower bound of TSMWDM are given below.

Step 1: Set $k = 1$, and choose an initial vector of Lagrangian multiplier denoted by $\boldsymbol{\lambda}^1$. Following the literature (Shore, 1985), a step-size, $\alpha_k = \frac{1}{k}$, $k = 1, 2, \ldots$, is adopted to ensure the global convergence of the approach, where k denotes the number of iterations.

Step 2: Solving (SLR) under $\boldsymbol{\lambda}^k$ for each w to derive the optimal solution $((\mathbf{x}_w^{k*})^T, (\mathbf{p}_w^{k*})^T, (\mathbf{z}_w^{k*})^T)^T$, we can calculate the subgradient $\beta_k = \sum_{w \in S} \mathbf{H}_w((\mathbf{x}_w^{k*})^T, (\mathbf{p}_w^{k*})^T, (\mathbf{z}_w^{k*})^T)^T$ and the objective function value $LR(\boldsymbol{\lambda}^k)$, respectively.

Step 3: Update the vector of Lagrangian multiplier using the subgradient information below.

$$\boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k + \alpha_k \beta_k \tag{50}$$

Step 4: The algorithm stops if the following criterion is reached.

$$\left| \frac{LR(\boldsymbol{\lambda}^{k+1}) - LR(\boldsymbol{\lambda}^k)}{LR(\boldsymbol{\lambda}^k)} \right| \leq \varepsilon \tag{51}$$

where ε is a given tolerance. Otherwise, set $k = k + 1$ and go to Step 2.

Obviously, relaxing Eqs. (45)-(46) and then using the dual decomposition and Lagrangian relaxation approach could also provide a lower bound for practical applications with a large number of 3PLs, lanes and possible disruptions, since the computing time might be reduced significantly.

To find robust solutions, a general scenario-based robust model shall be constructed under the robust optimization framework which includes two types of robustness, that is solution robustness and model robustness being used to ensure the optimality and feasibility of the solution in all scenarios, respectively. With a slight abuse of notations, let $\psi = \mathrm{E}[g(\mathbf{x}, \mathbf{p}, \mathbf{z}, \mathbf{y}, \mathbf{w})] = \sum_{w \in S} r_w \psi_w$, where $g(\mathbf{x}, \mathbf{p}, \mathbf{z}, \mathbf{y}, \mathbf{w})$ is the overall cost function of scenario w, ψ and ψ_w are the average cost values of all scenarios and the cost value of scenario w. The details of the model is given below (Mirzapour Al-E-Hashem et al., 2011).

$$\min \sum_{w \in S} r_w [\varpi_1 \psi_w + \varpi_1 \lambda(\psi_w + 2\theta_w - \sum_{w \in S} r_w \psi_w) + \varpi_2 \varphi_w] \tag{52}$$

$$\text{s.t.} \qquad \psi_w - \sum_{w \in S} r_w \psi_w + \theta_w \geq 0, \quad \forall w \in S \tag{53}$$

$$By_w + \varphi_w = d, \qquad \forall w \in S \tag{54}$$

$$\theta_w \geq 0, \qquad \forall w \in S \tag{55}$$

$$\varphi_w \geq 0, \qquad \forall w \in S \tag{56}$$

$$(\mathbf{x}, \mathbf{p}, \mathbf{z}, \mathbf{y}) \in \Gamma, \qquad \forall w \in S \tag{57}$$

where λ denotes the weight devoted to the solution variance, ϖ_1 and ϖ_2 denote the weights of the solution robustness and the method robustness, respectively, and Γ is a feasible domain obtained by solving Eqs. (2)-(3) and (6)-(13). More details of Eqs. (52)-(57) can be referred to Mulvey et al. (1995) and Pan & Nagi (2010).

5. Numerical experiments

To illustrate the performance of the proposed model and method, numerical experiments are conducted. Specifically, Section 5.1 presents the randomly generated instances for each problem tested. In Section 5.2, we show the effectiveness of the scenario reduction method by comparing it with the full scenario method. In Section 5.3, the fortification strategy is analyzed. Section 5.4 presents the numerical results of the extended models to show the robustness of the method. All the tests are solved using CPLEX 12.6.1 with a laptop of Intel(R) Core(TM) i5-3360M 2.80GHz CPU processor using 8 GB of RAM. In the numerical experiments, the algorithm stops either when the CPLEX solver displays "'N/A' due to the out of memory condition or when the running time reaches 3 hours.

5.1. Problem instance generation

For small scale problems[4], we assume that the 4PL serves 5 lanes and 10 3PLs who are willing to submit bids with 2 packages. The demand of each lane is 500, and the maximum fortification budget is 10000. The requirements of the minimum and maximum number of winning 3PLs are assumed to be 0 and 10, respectively. The bid price of each 3PL for each package on each lane follows a uniform distribution on the support [50, 100]. The fortification cost of each 3PL for each package follows a uniform distribution on the support [1000, 2000]. The fixed transaction cost of relationship management of each 3PL follows a uniform distribution on the support [2000, 3000]. The maximum shipment volume of each 3PL for each package on each lane follows a uniform distribution on the support [50, 100]. If the package of the 3PL is fortified, then the maximum extended shipment volume of each 3PL for each package on each lane is assumed to follow a uniform distribution on the support [10, 20]. The unit holding cost of the reservation shipment volume of each 3PL for each package on each lane follows a uniform distribution [100, 150].

The bidding packages of 3PLs are presented as [no. of 3PL, {package 1}, {package 2}], that is, [1, {1}, {1, 2}], [2, {2}, {2, 3}], [3, {3}, {3, 4}], [4, {4}, {4, 5}], [5, {5}, {1, 5}], [6, {1, 3}, {1, 2}], [7, {2, 3}, {2, 5}], [8, {3, 4}, {3, 5}], [9, {5}, {1}], [10, {2}, {4}]. The disrupted packages are assumed to be varied and can be described as [number of possible disrupted packages, {(no. of 3PL, no. of package)}, disruption probability vector], i.e., [5, {(4, 2), (5, 2), (7, 2), (8, 2), (9, 1)}, $(0.7, 0.9, 0.6, 0.4, 0.5)^T$], [8, {(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (7, 2), (8, 2), (9, 1)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.5, 0.6)^T$], [10, {(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (6, 2), (7, 2), (8, 2), (9, 1), (10, 2)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5)^T$], [12, {(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (6, 2), (7, 2), (8, 2), (9, 1), (9, 2), (10, 1), (10, 2)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5, 0.9, 0.7)^T$], [15, {(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (6, 1), (6, 2), (7, 1), (7, 2), (8, 1), (8, 2), (9, 1), (9, 2), (10, 1), (10, 2)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5, 0.9, 0.7, 0.6, 0.85, 0.5)^T$].

Given 5 possible disruptions of the small scale problems, using Eqs. (36)-(41), the full scenarios can be reduced as shown in Fig. 1. The first green line on the left-hand side represents that no package is disrupted, and the last green line on the right-hand side is the scenario in which all packages would be disrupted.

From Fig. 1, we see that 32 scenarios are reduced to 4 scenarios, which shows the effectiveness of the scenario reduction method. For other dimension of possible disruptions, the details of the reduced scenarios are shown in Table A.10.

[4] The data of large scale problems are presented in Appendix B

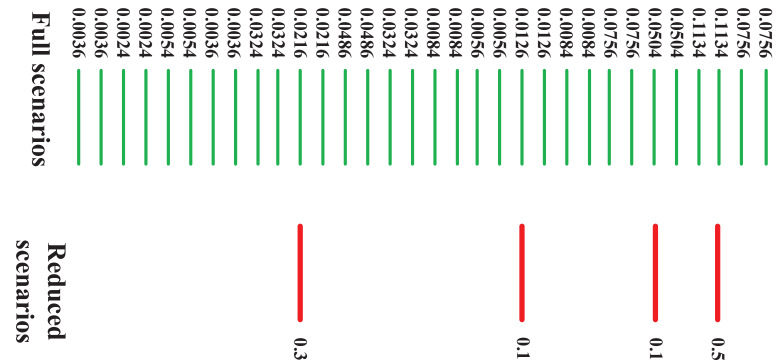

Figure 1: Comparison of full scenarios and reduced scenarios for 5 possible disrupted packages

5.2. Comparison analysis

Let "FS" denote the full scenario approach in which all scenarios would be investigated to derive the optimal solution for TSMWDM, and "RS" denote the reduced scenario approach in which the representative scenarios derived from Eqs. (36)-(41) are used to obtain the optimal solution for TSMWDM in this subsection. Given a set of possible disruptions as {5, 8, 10, 12, 15}, the results of the full and reduced scenarios for small and large scale problems are shown in Table 1.

Table 1: Comparison of full and reduced scenarios for different possible disruptions

Problem	Methodology	Possible disruptions	Number of scenarios	Total cost	Outside option	Selected packages	Number of fortifications	Time (s)
Small	FS	5	32	234517.15	135540	9	2	7
		8	256	236687.43	156890	8	3	10
		10	1024	238508.21	167760	7	4	15
		12	4096	239707.54	171000	7	4	40
		15	32768	239846.27	167760	7	5	290
	RS	5	4	234517.15	135540	9	2	5
		8	5	236687.43	156890	8	3	4.7
		10	5	238508.21	167760	7	4	4.5
		12	7	239707.54	171000	7	4	4.8
		15	9	239846.27	167760	7	5	5.4
Large	FS	5	32	796659.91	139570	30	1	12
		8	256	798410.39	139570	30	2	49
		10	1024	799997.54	139570	30	3	200
		12	4096	803654.44	139570	30	5	537
		15	32768	N/A	N/A	N/A	N/A	N/A
	RS	5	4	796659.91	139570	30	1	6.9
		8	5	798410.39	139570	30	2	7.3
		10	5	799997.54	139570	30	3	8.7
		12	7	803654.44	139570	30	5	10
		15	9	807904.56	178660	29	5	8.18

From Table 1, we see that the scenarios can be reduced substantially under RS by comparison with FS, and the numerical results show that there is no gap between FS and RS, that is, the total cost, the outside option cost, the winning packages and the fortified packages are the same for both approaches. We also see that when the dimension of the possible disruptions is 15, adopting FS cannot obtain the optimal solution in an effective time. Yet, RS could give a best solution very quickly, that is, the computing time of RS can be reduced tremendously, especially for large scale problems. Intuitively, when the dimension of possible disruptions increases, the 4PL would cost more to conduct the procurement and disruption mitigation activities, so the number of fortified packages and the outside option cost are likely to increase. Yet, to minimize the total cost, the 4PL has to make a trade-off between the protection cost and the outside option cost. Obviously, the 4PL would have a higher chance to adopt the fortification strategy or the outside option depending on whether the unit outside option cost is relatively high or low. Hence, when the number of fortified packages increases as the dimension of disruption increases, the outside option cost might decrease.

Given the case of 10 possible disrupted packages and a fixed set of the unit outside option costs $e \in \{100, 125, 150, 200, 300, 500, 1000\}$, the comparison of full and reduced scenarios for small and large scale problems is shown in Table 2.

Table 2: Comparison of full and reduced scenarios as outside option cost varies under 10 possible disruptions

Problem	Methodology	Unit outside option cost	Total cost	Outside option	Selected packages	Number of fortifications	Time (s)
Small	FS	100	238508	167760	7	4	15
		125	271589	146500	10	6	13
		150	300889	175810	10	6	11
		200	358656	225130	10	6	12
		300	458804	295100	10	7	12
		500	654303	486430	10	7	12
		1000	1140735	972870	10	7	12
	RS	100	238508	167760	7	4	4
		125	271589	146500	10	6	4
		150	300889	175810	10	6	4
		200	358656	225130	10	6	4
		300	458804	295100	10	7	4
		500	654303	486430	10	7	4
		1000	1140735	972870	10	7	4
Large	FS	100	799997.54	139570	30	3	200
		125	822367.63	66802	35	5	336
		150	831804.6	46534	36	6	474
		200	840845	27023	36	5	390
		300	848928	22890	38	5	485
		500	862479	32516	38	6	420
		1000	892934	59587	37	6	422
	RS	100	799997.54	139570	30	3	8
		125	822367.63	66802	35	5	8
		150	831804.6	46534	36	6	8
		200	840845	27023	36	5	8
		300	848928	22890	38	5	12
		500	862479	32516	38	6	13
		1000	892934	59587	37	6	15

From Table 2, we also see that the computing time is less under RS than under FS, especially for large scale problems. As the unit cost of the outside option increases, the 4PL would spend more to serve clients. Intuitively, the outside option strategy would have a lower chance to be utilized if the unit outside option cost becomes higher. Yet, since the 4PL has to make a trade-off between the fortification cost and the outside option cost, the outside option cost might increase as the unit outside option cost increases.

To further verify the performance of the scenario reduction approach, we use the Combinatorial Auction Test Suite (CATS)[5] to generate more realistic instances including 40 lanes and 80 3PLs with 5 packages for each bidder to show the effectiveness of RS. Given $d = 2000$, $c_{\max} = 15000$ and the possible disrupted packages as [5, {(63, 4), (58, 3), (38, 1), (80, 4), (79, 5)}, $(0.7, 0.9, 0.6, 0.4, 0.5)^T$], [10, {(26, 1), (33, 1), (38, 1), (66, 2), (69, 2), (58, 3), (20, 4), (51, 4), (63, 4), (70, 4)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5)^T$], and [15, {(26, 1), (33, 1), (38, 1), (66, 2), (69, 2), (58, 3), (20, 4), (51, 4), (63, 4), (70, 4), (70, 5), (71, 1), (72, 1), (73, 1), (74, 1)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5, 0.9, 0.7, 0.6, 0.85, 0.5)^T$], the results are shown below. In Table 3, PD denotes possible disruptions, UC denotes

[5] https://www.cs.ubc.ca/∼kevinlb/CATS/CATS-readme.html

the unit outside option cost, TC denotes total cost, OC denotes the outside option cost, SP denotes the number of selected packages, NF denotes the number of fortified packages, UB denotes the upper bound derived based on scenario reduction approach, Gap denotes the gap between UB and the optimal solution obtained by the full scenario method, LBP denotes the lower bound derived by relaxing the original problem, i.e., setting $q_{jkw} = 0$ for all $w \in S$, ULGP denotes the gap between UB and LBP, LBM denotes the lower bound derived by using the dual decomposition and Lagrangian relaxation approach as mentioned in Section 4, and ULGM denotes the gap between UB and LBM.

Table 3: Comparison of full and reduced scenarios as outside option cost varies for the case of 80 3PLs and 40 lanes

PD	UC	Full scenarios (FS)					Reduced scenarios (RS)					Performance					
		TC	OC	SP	NF	Time (S)	TC	OC	SP	NF	Time (S)	UB	Gap (%)	LBP	ULGP (%)	LBM	ULGM (%)
5	100	5920487	5005400	65	1	3546	5920537	4961700	66	1	181	5920537	0.001	5915861	0.079	5919073	0.025
	125	6760748	2332500	80	4	324	6761072	2327700	80	4	24	6761072	0.005	6749259	0.175	6757325	0.055
	150	6986410	365490	80	4	2258	6896164	384940	80	4	62	6986164	-0.004	6974920	0.161	6982635	0.051
	200	6999556	0	80	4	3696	6999556	0	80	4	89	6999556	0	6988066	0.164	6995931	0.052
	300	6999556	0	80	4	3696	6999556	0	80	4	88	6999556	0	6988066	0.164	6995933	0.052
	500	6999556	0	80	4	3696	6999556	0	80	4	88	6999556	0	6988066	0.164	6995931	0.052
	1000	6999556	0	80	4	3696	6999556	0	80	4	89	6999556	0	6988066	0.164	6995931	0.052
10	100	N/A	N/A	N/A	N/A	N/A	5924857	4983600	66	2	110	5924857	N/A	5915861	0.152	5920976	0.066
	125	N/A	N/A	N/A	N/A	N/A	6770708	2426000	80	4	34	6770708	N/A	6749259	0.317	6763540	0.106
	150	N/A	N/A	N/A	N/A	N/A	7002004	333010	80	5	125	7002004	N/A	6974920	0.387	6990783	0.160
	200	N/A	N/A	N/A	N/A	N/A	7014800	0	80	5	318	7014800	N/A	6988066	0.381	7003706	0.158
	300	N/A	N/A	N/A	N/A	N/A	7014800	0	80	5	343	7014800	N/A	6988066	0.381	7003703	0.158
	500	N/A	N/A	N/A	N/A	N/A	7014800	0	80	5	359	7014800	N/A	6988066	0.381	7003705	0.158
	1000	N/A	N/A	N/A	N/A	N/A	7014800	0	80	5	370	7014800	N/A	6988066	0.381	7003705	0.158
15	100	N/A	N/A	N/A	N/A	N/A	5930325	4975200	66	4	205	5930325	N/A	5915861	0.244	5924577	0.097
	125	N/A	N/A	N/A	N/A	N/A	6780030	2492000	80	5	60	6780030	N/A	6749259	0.454	6767284	0.188
	150	N/A	N/A	N/A	N/A	N/A	7013815	294190	80	5	164	7013815	N/A	6974920	0.555	6996085	0.253
	200	N/A	N/A	N/A	N/A	N/A	7025939	0	80	5	568	7025939	N/A	6988066	0.539	7008798	0.244
	300	N/A	N/A	N/A	N/A	N/A	7025939	0	80	5	558	7025939	N/A	6988066	0.539	7008796	0.244
	500	N/A	N/A	N/A	N/A	N/A	7025939	0	80	5	565	7025939	N/A	6988066	0.539	7008796	0.244
	1000	N/A	N/A	N/A	N/A	N/A	7025939	0	80	5	572	7025939	N/A	6988066	0.539	7008796	0.244

From Table 3, we see that for the case of 5 possible disruptions, when the unit outside option cost is low, RS might be slightly worse than FS in terms of the solution quality, but the gap is always very small. When there are 10 or 15 possible disruptions, since the gaps between the upper bound and two different lower bounds (i.e., LBP and LBM) are also small, we see that RS can provide a good approximation very quickly, whereas FS cannot give an effective solution in more than 90 hours. It is worth noting that for all the tested problems generated in Section 5, no gap exists between FS and RS if the lower bound is not mentioned. Hence, we may conclude that the scenario reduction approach performs better than the full scenario method. Although the quality of LBM is better than that of LBP, the computing time of the former is much longer, and thereby it would be better to obtain a lower bound by relaxing the original problem first than by using the dual decomposition and Lagrangian relaxation approach. In summary, the scenario reduction approach is effective and applicable for the 4PL to manage the total cost of protection, reservation, outside option and expected procurement simultaneously. Also, the results confirm that TSMWDM could be a useful tool for the 4PL to purchase transportation services from 3PLs and identify the best possible protection strategies simultaneously.

5.3. Mitigation strategy analysis

Recall that the hybrid strategies including outside option, fortification, and reservation measures denoted by "OFRS" are investigated simultaneously to mitigate the disruptions, and the results are shown in Table 2. Next, we assume that the 4PL would only adopt the outside option strategy denoted by "OS", or adopt the outside option and fortification strategies denoted by "OFS" to show the effectiveness of OFRS. Indeed, we could derive OS by letting $x_{jk} = 0$ and OFS by letting $z_{ijk} = 0, \forall\ i \in I,\ j \in J,\ k \in K_j$. Given the case of 10 possible disrupted packages and a fixed set of the unit outside option cost $e \in \{100, 125, 150, 200, 300, 500, 1000\}$, the results are shown in Table 4.

Table 4: Comparison of different mitigation strategies for the large scale problem under 10 possible disruptions

	OS			OFS			
Unit outside option cost	Total cost	Outside option	Selected packages	Total cost	Outside option	Selected packages	Number of fortification
100	816618	187590	30	799997.54	139570	30	3
125	854766	142980	33	822367.63	66802	35	5
150	881717	159540	34	831804	46543	36	6
200	934644	194920	35	841355	32390	36	5
300	1026547	274270	38	853714	36768	38	5
500	1209391	457110	38	878227	61280	38	5
1000	1664440	908780	37	937446	117120	37	5

From Table 4, we see that as the unit outside option cost increases, the 4PL's total cost increases for OS and OFS, which follows the same pattern as OFRS as shown in Table 2. Intuitively, the number of winning packages is higher under OS than that under OFS. Yet, to reduce the transaction cost of relationship management associated with the winning 3PLs, the 4PL would prefer to select 3PLs with larger capacity, and thereby the number of winning packages under OS could be less than those under OFS (see the fourth and seventh columns in Table 4). Similarly, since the disrupted package might be fortified to expand its capacity, the number of fortified packages would generally be less under OFRS than under OFS for fixed demand. Yet, given the relatively high outside option cost, to minimize the total cost by reducing the outside option cost and expanding the capacity of 3PLs with a low bid price, the 4PL may want to fortify more packages under OFRS than under OFS, especially when the demand is relatively high (see the last column in Table 4 and the seventh column in Table 2).

Also, we see that the total cost under OS is higher than that under OFS (see the second and fifth columns in Table 4), which means that the 4PL would cost more money if the outside option strategy is simply adopted. In the meanwhile, we find that the total cost under OFS could be higher than that under OFRS, especially for the case of high unit outside option cost, which means that OFRS is the best option for the 4PL to mitigate disruptions. The analysis shows that our proposed model, i.e., TSMWDM, can be used to identify core sets of packages to be fortified, determine suitable extended capacity pre-positioned in fortified packages, and choose appropriate outside options simultaneously to mitigate the disruptions while conducting the TSP activity. Obviously, there is an optimal trade-off point across the mitigation strategies of the outside option, fortification and reversion. The results also confirm that the proposed model and hybrid mitigation strategy are significant to achieve the goal of cost minimization for the TSP of 4PLs via CRA.

Given a set of demand $d \in \{300, 500\}$, disruption probabilities $p \in \{0, 0.1, 0.3, 1\}$, and the unit outside option cost $e \in \{100, 125, 150, 200, 300, 500, 1000\}$, the results are shown in Table 5. When $d \in \{100, 700\}$, the results are shown in Table A.11.

From Tables 5 and A.11, we see that as the disruption probability increases, the package would have a higher chance to be fortified. Intuitively, when the disruption probability is low, the packages would generally not be fortified, especially for the setting of low demand and low unit outside option cost (see

Table 5: Results of large scale problems as disruption probability varies under 10 possible disruptions

d	Disruption probability	Unit outside option cost	Total cost	Outside option	Selected packages	Number of fortifications
300	0	100	449327	28590	23	0
		125	451883	4116	25	0
		150	452567	3849.6	25	0
		200	452567	3849.6	25	0
		300	452567	3849.6	25	0
		500	453297	0	25	0
		1000	453297	0	25	0
	0.1	100	452627	35092	23	0
		125	456513	8412	25	1
		150	457574	5782	25	2
		200	458888	165	25	3
		300	458903	0	25	2
		500	458903	0	25	2
		1000	458903	0	25	2
	0.3	100	455004	32209	23	3
		125	457843	4116	25	4
		150	458527	3849	25	4
		200	458903	0	25	2
		300	458903	0	25	2
		500	458903	0	25	2
		1000	458903	0	25	2
	1	100	455287	28590	23	4
		125	457843	4116	25	4
		150	458527	3849	25	4
		200	458903	0	25	2
		300	458903	0	25	2
		500	458903	0	25	2
		1000	458903	0	25	2
500	0	100	794117	121220	31	0
		125	813890	66177	35	0
		150	823272	46543	36	0
		200	833504	32390	36	0
		300	845499	26183	38	2
		500	858708	29794	38	5
		1000	888502	59587	38	5
	0.1	100	798322	130610	31	1
		125	820732	71710	35	3
		150	831220	53183	36	3
		200	840790	30739	36	4
		300	848928	22890	38	5
		500	862479	32516	38	6
		1000	892934	59587	37	6
	0.3	100	799997	139570	30	3
		125	822367	66802	35	5
		150	831804	46543	36	6
		200	840845	27023	36	5
		300	848928	22890	38	5
		500	862479	32516	38	6
		1000	892934	59587	37	6
	1	100	799997	139570	30	3
		125	822367	66802	35	5
		150	831804	46543	36	6
		200	840845	27023	36	5
		300	848928	22890	38	5
		500	862479	32516	38	6
		1000	892934	59587	37	6

$p \in \{0, 0.1\}$ and $d \in \{100, 300\}$). Yet, to satisfy the high demand of clients, the package with a low bid price might be fortified to expand its capacity for reservation, especially when the unit outside option cost becomes high (see $p = 0$ and $d \in \{500, 700\}$). Since the 4PL has to pay for utilizing the mitigation strategy, when the disruption probability increases, more packages would be fortified and pre-positioned, and the outside option would have a larger probability to be adopted if the unit outside option cost is low. However, when the unit outside option cost is high, the fortification strategy becomes more important than the outside option strategy, and thereby the outside option strategy would have a smaller probability to be adopted. This analysis indicates that if the probability of disruption is observed to be higher, then the hybrid mitigation strategy becomes more important for cost minimization, which further shows the effectiveness of the proposed strategy.

Given a set of demand $d = \{100, 300, 500, 700\}$ and a fixed number of 3PLs $N_{\min} \in \{0, 5, 20, 35\}$, $N_{\max} \in \{5, 20, 35, 40\}$, the results are shown in Table 6.

Table 6: Results of large scale problems as demand and N varies under 10 possible disruptions

d	$N_{\min}$	$N_{\max}$	Total cost	Outside option	Selected packages	Number of fortifications
100	0	5	169648	80000	5	0
		20	152721	0	12	1
		35	152721	0	12	1
		40	152721	0	12	1
	5	20	152721	0	12	1
		35	152721	0	12	1
		40	152721	0	12	1
	20	35	165614	0	20	1
		40	165614	0	20	1
	35	40	198153	0	35	1
300	0	5	538996	377810	5	0
		20	456235	51509	20	2
		35	455287	28590	23	4
		40	455287	28590	23	4
	5	20	456235	51509	20	2
		35	455287	28590	23	4
		40	455287	28590	23	4
	20	35	455287	28590	23	4
		40	455287	28590	23	4
	35	40	474925	3580.8	35	4
500	0	5	936644.8	749140	5	0
		20	819405.94	257870	20	3
		35	799997.54	139570	30	3
		40	799997.54	139570	30	3
	5	20	819405.94	257870	20	3
		35	799997.54	139570	30	3
		40	799997.54	139570	30	3
	20	35	799997.54	139570	30	3
		40	799997.54	139570	30	3
	35	40	805808.17	97602	35	5
700	0	5	1336644	1149160	5	0
		20	1209370	578840	20	3
		35	1172946	346160	33	4
		40	1172946	346160	33	4
	5	20	1209370	578840	20	3
		35	1172946	346160	33	4
		40	1172946	346160	33	4
	20	35	1172946	346160	33	4
		40	1172946	346160	33	4
	35	40	1173902	315470	35	5

From Table 6, we see that for a given fixed $N_{\min}$ and $N_{\max}$, the number of fortified packages is more likely to increase as the demand increases. Intuitively, given the number of minimum available 3PLs being 0, when the number of maximum available 3PLs increases, the undisturbed packages could have a higher chance to be selected and the number of fortified packages is likely to be reduced. Yet, if the capacity of the undisturbed packages is insufficient, fortifying the disrupted packages could benefit the buyer. Also, we find that on the one hand, when the demand is higher than the total capacity of the maximum available 3PLs, the outside option would be adopted to satisfy the demand, and the 4PL generally pays more (see the first row of Table 6 for $d = 100$). On the other hand, when the number of minimum available 3PLs is high, 3PLs with a high bid price would be involved and the 4PL has to spend more (see the last three rows of Table 6 for $d = 100$). This analysis implies that appropriately setting the numbers of maximum and minimum available 3PLs is important for the 4PL to reduce the total cost.

Given a set of demand $d = \{300, 500\}$, the protection investment budget $C_{\max} \in \{2000, 5000, 10000, 15000\}$, and the unit outside option cost $e \in \{100, 125, 150, 200, 300, 500, 1000\}$, the results are shown in Table 7. When $d = 700$, the results are shown in Table A.12.

Table 7: Results of large scale problems as demand and $C_{\max}$ vary under 10 possible disruptions

d	$C_{\max}$	Unit outside option cost	Total cost	Outside option	Selected packages	Number of fortifications
300	2000	100	460476	59867	21	1
		125	466796	21932	25	1
		150	471182	26319	25	1
		200	476338	15267	26	1
		300	483971	22900	26	1
		500	497855	31948	26	1
		1000	529803	63895	26	1
	5000	100	455297.75	29415	22	3
		125	458059.9	5147.1	24	3
		150	458821.65	3849.6	25	2
		200	458903	0	25	2
		300	458903	0	25	2
		500	458903	0	25	2
		1000	458903	0	25	2
	10000	100	455287	28590	23	4
		125	457843.01	4116	25	4
		150	458527	3849.6	25	4
		200	458903.4	0	25	2
		300	458903.4	0	25	2
		500	458903.4	0	25	2
		1000	458903.4	0	25	2
	15000	100	455287	28590	23	4
		125	457843.01	4116	25	4
		150	458527	3849.6	25	4
		200	458903.4	0	25	2
		300	458903.4	0	25	2
		500	458903.4	0	25	2
		1000	458903.4	0	25	2
500	2000	100	808945.23	164630	30	1
		125	841352	114270	33	1
		150	862561	125100	34	1
		200	901721	139320	35	1
		300	966764	192230	38	1
		500	1094921	320390	38	1
		1000	1413252	635340	37	1
	5000	100	799997.54	139570	30	3
		125	826311.32	101540	33	3
		150	840225	70740	35	3
		200	861270	67655	36	3
		300	889668	83837	38	3
		500	944548	136770	38	3
		1000	1079255	268090	37	3
	10000	100	799997.54	139570	30	3
		125	822367.63	66802	35	5
		150	831804.6	46534	36	6
		200	840845	27023	36	5
		300	848928	22890	38	5
		500	862479	32516	38	6
		1000	892934	59587	37	6
	15000	100	799997.54	139570	30	3
		125	822367.63	66802	35	5
		150	831804	46534	36	6
		200	840845	27023	36	5
		300	848928	22890	38	5
		500	861892	29794	38	7
		1000	891686	59587	38	7

From Tables 7 and A.12, we see that if the fortification budget is sufficient, then the outside option strategy would become less important for dealing with disruptions than the fortification strategy, especially when the unit outside option cost is high. In this case, the fortification strategy can not only be adopted to mitigate disruptions, but also can be utilized to expand the capacity of the packages. Hence, the 4PL would spend less in serving clients, especially when the demand is high. If the fortification budget is insufficient, then the outside option strategy becomes more important, especially when the unit outside option cost is low. In this case, the 4PL is more likely to resort to the outside option for mitigating disruptions, and thereby the total cost of 4PLs might increase. This analysis indicates that an adequate fortification budget could benefit the 4PL.

5.4. Numerical experiments of extended models

Applying the scenario reduction approach to solve the extended models, we would verify the robustness of the method as shown below.

5.4.1. Partially disrupted packages

Other data being the same as our basic model of the small scale problem, given $d = 300$, the probably disrupted capacity of lanes described as [number of possible disrupted lanes in terms of capacity, $\{$(no. of 3PL, no. of lane)$\}$, disruption probability vector] are assumed to be [5, $\{(1, 2), (2, 3), (3, 4), (4, 5), (7, 5)\}$, $(0.7, 0.9, 0.6, 0.4, 0.5)^T$]. Given FD denoting the probability that the fortified lanes in terms of capacity might be disrupted, SL denoting the number of selected lanes and FL denoting the number of fortified lanes associated with capacity, the results of the extended model are shown below.

Table 8: Comparison of full and reduced scenarios as outside option cost varies for capacity disruption of lanes

FD	UC	Full scenarios (FS)					Reduced scenarios (RS)					Performance	
		TC	OC	SL	FL	Time (S)	TC	OC	SL	FL	Time (S)	UB	Gap (%)
0.1	100	143029.7	59093	9	1	9.7	142909.8	58643	9	1	4.38	143029.7	0
	125	154613.8	42912	10	3	9.88	154573.8	51529	10	2	4.72	154806.2	0.1244
	150	162511.1	46748	10	4	9.27	162511.1	46748	10	4	4.43	162511.1	0
	200	175742.4	50285	10	5	9.43	175742.4	50285	10	5	4.41	175742.4	0
	300	197531.2	58936	10	5	9.35	197531.2	58936	10	5	4.48	197531.2	0
	500	230932.4	82649	10	7	10.15	230932.4	82649	10	7	4.3	230932.4	0
	1000	313581.7	165300	10	7	9.98	313581.7	165300	10	7	4.43	313581.7	0
0.2	100	143253.2	59626	9	1	9.11	143133.2	59177	9	1	4.33	143253.2	0
	125	155326.7	48481	10	2	9.14	155209.9	52717	10	2	4.29	155442.0	0.0742
	150	163933.1	49286	10	4	10.34	163933.1	49286	10	4	4.39	163933.1	0
	200	178413.5	56145	10	5	10.22	178413.5	56145	10	5	4.41	178413.5	0
	300	203550.9	70419	10	5	10.38	203550.9	70419	10	5	4.35	203550.9	0
	500	243061.6	96701	10	7	10.9	243061.6	96701	10	7	4.43	243061.6	0
	1000	339762.8	193400	10	7	10.22	339762.8	193400	10	7	4.38	339762.8	0

From Table 8, we see that the gap between RS and FS is very small, and hence RS still works for the problem of capacity disruption associated with lanes in a package. It is worth noting that we also conduct the numerical experiments for $d = 500$, and there is no gap under the same structure of Table 8. The result verifies the effectiveness and applicability of the scenario reduction approach and the proposed framework for the two-stage stochastic winner determination problem under disruptions.

5.4.2. No execution risk of 3PLs

Using the data of our basic model for the small scale problem with 5 possible disruptions, given PC denoting the penalty cost, the numerical results are shown below.

From Table 9, we see that the gap between RS and FS is zero, and hence RS still works for the problem with no execution risk. The result verifies the effectiveness and applicability of the scenario reduction approach.

Table 9: Comparison of full and reduced scenarios as outside option cost varies with no execution risk

d_i	UC	Full scenarios (FS)					Reduced scenarios (RS)					Performance	
		TC	OC	PC	SP	Time (S)	TC	OC	PC	SP	Time (S)	UB	Gap (%)
300	100	126810.6	66766	24878	10	4.1	126809.8	66754	24878	10	4.1	126810.6	0
	125	142124.1	65275	16896	10	4.02	142069.8	65130	16896	10	3.87	142124.1	0
	150	154094.8	54780	9743.1	10	4.46	154094.8	54780	9743.1	10	4.17	154094.8	0
	200	171406.4	65557	5543	10	5.38	171406.4	65557	5543	10	4.39	171406.4	0
	300	204184.9	98335	5543	10	4.97	204184.9	98335	5543	10	4.33	204184.9	0
	500	267668.4	155330	0	10	5.01	267668.4	155330	0	10	4.06	267668.4	0
	1000	422994.4	310650	0	10	4.97	422994.4	310650	0	10	4.32	422994.4	0
500	100	226809.7	166750	24878	10	4.56	226809.7	166750	24878	10	4.22	226809.7	0
	125	266886.7	189700	16896	10	4.6	266886.7	189700	16896	10	4.48	266886.7	0
	150	303284.6	198280	9743.1	10	4.57	303284.6	198280	9743.1	10	4.36	303284.6	0
	200	368430.2	256890	5543	10	4.43	368430.2	256890	5543	10	4.16	368430.2	0
	300	496876.6	385340	5543	10	5.01	496876.6	385340	5543	10	4.35	496876.6	0
	500	751695.87	633670	0	10	4.56	751695.87	633670	0	10	4.33	751695.87	0
	1000	1385361.4	1267300	0	10	4.38	1385361.4	1267300	0	10	4.26	1385361.4	0

6. Conclusions

Since the reverse auction can reduce the procurement and transaction cost of buyers, it has been increasingly utilized for practical applications. This paper considers the combinatorial reverse auction activity in which a 4PL acting as an auctioneer solicits bids from a group of 3PLs for transportation service procurement. Without loss of generality, we assume that 3PLs submit XOR bids, that is, each 3PL submits a bid that involves multiple packages, but can win at most one package. Noting that in practice, some packages could be disrupted due to accidental risks such as equipment breakdowns, power outage, supplier discontinuities and industrial incidents, we particularly investigate a novel winner determination problem involving disruptions associated with 3PLs. We demonstrate how fortification, reservation and outside option strategies can be integrated with combinatorial reverse auctions to obtain an optimal procurement strategy for the 4PL.

Considering a limited protection investment budget, we propose a two-stage stochastic mixed-integer winner determination model to solve the problem from the 4PL's point of view. In the first-stage, the 4PL minimizes the sum of the fortification cost of the 3PLs' packages and the expected cost related to different disruption scenarios. In the second stage, the 4PL tries to select the winning 3PLs to fulfill the demand of clients under each disruption scenario by minimizing the total cost of procurement, holding reservation capacity, transaction for relationship management associated with winning 3PLs, and outside option of utilizing 3PLs not included in the auction simultaneously. Since the deterministic equivalent reformulation of the proposed model would involve a large number of variables and constraints under huge disruption scenarios, it cannot be solved directly. Hence, a scenario reduction approach is applied to obtain representative scenarios, and then the deterministic equivalent reformulation can be solved by CPLEX solver directly. Relaxing the original problem or adopting an efficient dual decomposition and Lagrangian relaxation approach, a lower bound could be obtained for evaluation of the scenario reduction approach.

Numerical experiments show that combining the hybrid mitigation strategy with combinatorial reverse auctions, the 4PL not only can assign the demand to the winning 3PLs, but also can identify core sets of packages to be fortified, determine pre-positioned capacity of fortified packages, and choose suitable outside options. By conducting comparison analysis, we find that the scenario reduction approach provides a good approximation for TSMWDM using the full scenario approach, which indicates the effectiveness and applicability of the method. Sensitivity analysis indicates that the hybrid mitigation strategy including fortification, reservation and outside option performs better than the other strategies, and thereby could be a useful tool for the 4PL to mitigate disruptions. Also, we find that the 4PL could benefit from appropriate numbers of maximum and minimum available 3PLs and an adequate protection investment budget. We also develop two extensions to consider the settings of partially disrupted packages and no execution risk, and verify the effectiveness and applicability of the cost reduction approach under each extended model.

Several related issues are interesting for future investigation. First, the demand of clients is assumed to be fixed in this paper. In relaxing this assumption to allow stochastic demand, solving the problem becomes more difficult. Yet, if the 4PL can have an estimate of the demand, then our analysis provides a suitable approximation. Second, this study assumes that both the 4PL and 3PLs are perfectly rational. In practical applications, when facing uncertainties, decision makers may involve bounded rationality such as loss aversion, fairness concerns and anticipated regret. Although constructing a new mathematical model is necessary, we may conjecture that the proposed hybrid mitigation strategy and the scenario reduction approach can be still worked.

Acknowledgments

This work has been sponsored by NSFC Grant #71801157; Natural Science Foundation of Department of Education of Guangdong Grant #2017KQNCX171; Natural Science Foundation of SZU Grant #2018059; NSFC Grant #71572115; and Major Program of Social Science Foundation of Guangdong Grant #2016WZDXM005. We are grateful to the editors and reviewers for their most valuable comments that help us improve the quality of work significantly.

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Appendix A. Supplemental tables for numerical results

Table A.10: Details of reduced scenarios for small scale problems

Problem	Possible disruptions	Reduced scenarios	Probability
Small	5	(4, 2), (5, 2), (7, 2), (9, 1)	0.5
		(5, 2), (8, 2)	0.3
		(4, 2), (5, 2), (8, 2)	0.1
		(4, 2), (7, 2)	0.1
	8	(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (7, 2), (9, 1)	0.45
		(1, 2), (4, 2), (8, 2)	0.3
		(2, 2), (5, 2), (7, 2), (8, 2), (9, 1)	0.15
		(2, 2), (4, 2), (7, 2)	0.05
		(1, 2), (2, 2), (3, 2), (4, 2), (7, 2), (8, 2)	0.05
	10	(1, 2), (2, 2), (4, 2), (5, 2), (6, 2), (7, 2), (8, 2), (10, 2)	0.5
		(2, 2), (3, 2), (4, 2), (6, 2), (7, 2), (9, 1)	0.2
		(1, 2), (3, 2), (4, 2), (7, 2), (9, 1)	0.15
		(1, 2), (3, 2), (5, 2), (8, 2)	0.1
		(1, 2), (3, 2), (7, 2), (9, 1)	0.05
	12	(1, 2), (2, 2), (4, 2), (5, 2), (6, 2), (7, 2), (8, 2), (9, 2), (10, 1), (10, 2)	0.35
		(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (6, 2), (7, 2), (8, 2), (10, 1), (10, 2)	0.25
		(1, 2), (2, 2), (3, 2), (4, 2), (6, 2), (7, 2), (9, 1), (9, 2), (10, 1), (10, 2)	0.1
		(3, 2), (9, 1)	0.1
		(1, 2), (4, 2), (7, 2), (9, 1), (10, 1)	0.1
		(4, 2), (7, 2), (9, 1), (9, 2), (10, 1)	0.05
		(3, 2), (7, 2), (9, 1), (10, 1)	0.05
	15	(1, 2), (2, 2), (4, 2), (5, 2), (6, 1), (6, 2), (7, 1), (8, 2), (9, 1), (9, 2), (10, 1)	0.3375
		(1, 2), (2, 2), (3, 2), (4, 2), (5, 2), (6, 1), (6, 2), (7, 1), (8, 1), (8, 2), (9, 1), (9, 2), (10, 1), (10, 2)	0.2625
		(1, 2), (2, 2), (3, 2), (4, 2), (6, 1), (6, 2), (7, 2), (8, 2), (9, 1), (10, 1)	0.1
		(1, 2), (4, 2), (6, 2), (7, 2), (8, 1), (8, 2), (10, 1), (10, 2)	0.1
		(7, 2), (8, 1), (10, 2)	0.0625
		(3, 2), (6, 2), (7, 2), (8, 1), (8, 2), (10, 2)	0.05
		(3, 2), (7, 2)	0.0375
		(3, 2), (4, 2), (6, 2), (7, 2), (8, 2), (10, 1), (10, 2)	0.025
		(3, 2), (4, 2), (6, 2), (7, 2), (8, 1), (8, 2), (10, 1)	0.025
Large	5	(7, 2), (17, 1), (18, 1), (40, 1)	0.5
		(17, 1), (32, 2)	0.3
		(7, 2), (17, 1), (32, 2)	0.1
		(7, 2), (18, 1)	0.1
	8	(7, 2), (8, 1), (8, 2), (16, 1), (17, 1), (18, 1), (40, 1)	0.45
		(7, 2), (16, 1), (32, 2)	0.3
		(8, 1), (17, 1), (18, 1), (32, 2), (40, 1)	0.15
		(8, 1), (16, 1), (18, 1)	0.05
		(7, 2), (8, 1), (8, 2), (16, 1), (18, 1), (32, 2)	0.05
	10	(7, 2), (8, 1), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (40, 1)	0.5
		(8, 1), (8, 2), (16, 1), (17, 1), (18, 1), (32, 2)	0.2
		(7, 2), (8, 2), (16, 1), (18, 1), (32, 2)	0.15
		(7, 2), (8, 2), (16, 2), (32, 1)	0.1
		(7, 2), (8, 2), (18, 1), (32, 2)	0.05
	12	(7, 2), (8, 1), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (39, 2), (40, 1), (40, 2)	0.35
		(7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (40, 1), (40, 2)	0.25
		(7, 2), (8, 1), (8, 2), (16, 1), (17, 1), (18, 1), (32, 2), (39, 2), (40, 1), (40, 2)	0.1
		(8, 2), (32, 2)	0.1
		(7, 2), (16, 1), (18, 1), (32, 2), (40, 1)	0.1
		(16, 1), (18, 1), (32, 2), (39, 2), (40, 1)	0.05
		(8, 2), (18, 1), (32, 2), (40, 1)	0.05
	15	(1, 2), (2, 2), (7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (32, 1), (32, 2), (39, 2), (40, 1)	0.3375
		(1, 2), (2, 2), (2, 3), (7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (18, 1), (32, 1), (32, 2), (39, 2), (40, 1), (40, 2)	0.2625
		(1, 2), (2, 2), (2, 3), (7, 2), (8, 2), (16, 1), (17, 1), (32, 1), (32, 2), (40, 1)	0.1
		(1, 2), (7, 2), (16, 1), (17, 1), (18, 1), (32, 1), (40, 1), (40, 2)	0.1
		(17, 1), (18, 1), (40, 2)	0.0625
		(2, 3), (16, 1), (17, 1), (18, 1), (32, 1), (40, 2)	0.05
		(2, 3), (17, 1)	0.0375
		(2, 3), (7, 2), (16, 1), (17, 1), (32, 1), (40, 1), (40, 2)	0.025
		(2, 3), (7, 2), (16, 1), (17, 1), (18, 1), (32, 1), (40, 1)	0.025

Appendix B. Data of large scale problems

For large scale problems, 20 lanes and 40 3PLs with at most 5 packages are considered. The bidding packages of 3PLs are [1, {2, 3}, {1, 11, 12}, {1, 15, 16}, {1, 17}, {1, 19}], [2, {1, 2}, {1, 2, 11, 12}, {2, 3, 15, 16}, {4, 5}, {16, 17, 18}], [3, {2, 3}, {4, 5, 6}, {19, 20}, {1, 19, 20}, {3, 17, 18}], [4, {5, 6}, {4, 5, 6}, {5, 6, 15}, {11, 12, 15}, {16, 17, 18}], [5, {3, 4, 5}, {2, 3, 11}, {4, 5, 6}, {11, 15, 16}, {18, 19, 20}],

Table A.11: Results of large scale problems as disruption probability varies under 10 possible disruptions

d	Disruption probability	Unit outside option cost	Total cost	Outside option	Selected packages	Number of fortifications
100	0	100	149807	0	12	0
		125	149807	0	12	0
		150	149807	0	12	0
		200	149807	0	12	0
		300	149807	0	12	0
		500	149807	0	12	0
		1000	149807	0	12	0
	0.1	100	151855	2000	12	0
		125	152355	2500	12	0
		150	152721	0	12	1
		200	152721	0	12	1
		300	152721	0	12	1
		500	152721	0	12	1
		1000	152721	0	12	1
	0.3	100	152721	0	12	1
		125	152721	0	12	1
		150	152721	0	12	1
		200	152721	0	12	1
		300	152721	0	12	1
		500	152721	0	12	1
		1000	152721	0	12	1
	1	100	152721	0	12	1
		125	152721	0	12	1
		150	152721	0	12	1
		200	152721	0	12	1
		300	152721	0	12	1
		500	152721	0	12	1
		1000	152721	0	12	1
700	0	100	1166563	323710	34	0
		125	1230739	272630	39	0
		150	1284034	294920	39	0
		200	1376956	370920	40	0
		300	1549615	494950	40	7
		500	1870949	800020	40	7
		1000	2666003	1573200	40	7
	0.1	100	1170880	334770	34	1
		125	1237129	278230	39	3
		150	1290988	294920	39	5
		200	1383119	357130	40	5
		300	1550265	494060	40	7
		500	1870949	800020	40	7
		1000	2669770	1597600	40	7
	0.3	100	1172946	346160	33	4
		125	1237693	272630	39	5
		150	1290988	294920	39	5
		200	1383119	357130	40	5
		300	1550265	494060	40	7
		500	1870949	800020	40	7
		1000	2669770	1597600	40	7
	1	100	1172946	346160	33	4
		125	1237693	272630	39	5
		150	1290988	294920	39	5
		200	1383119	357130	40	5
		300	1550265	494060	40	7
		500	1870949	800020	40	7
		1000	2669770	1597600	40	7

[6, {11}, {17}, {20}, {5, 6}, {3, 4}], [7, {11, 12}, {13, 14}, {7, 13}, {19}, {20}], [8, {7}, {8}, {11}, {16}, {19}], [9, {5, 6}, {3}, {4}, {15, 16}, {1, 3}], [10, {11, 12}, {15, 16}, {17, 18, 19}, {19}, {20}], [11, {16}, {17}, {18}, {2, 15}, {1, 16}], [12, {3, 4, 5}, {15, 16, 17}, {11, 12, 15}, {17, 18, 19}, {2, 4, 5}], [13, {15}, {11}, {12}, {12, 15}, {17}], [14, {3}, {4}], [15, {16}, {17}], [16, {9, 10}, {7, 8}], [17, {13, 14}], [18, {7, 9}], [19, {17}, {18}], [20, {5}, {6}], [21, {2, 3}, {3}], [22, {16, 17}], [23, {18, 19}], [24, {20}], [25, {19}], [26, {11}], [27, {12}], [28, {1, 4}, {5, 6}], [29, {13}, {14}], [30, {16, 17, 18}], [31, {18, 19}], [32, {7, 8}, {9}], [33, {1, 2}, {1, 16}, {1, 17}], [34, {2, 3}, {2, 16}], [35, {5, 8}], [36, {17, 18}, {19}], [37, {5, 6}, {11, 12, 15}], [38, {17}, {10}], [39, {15, 19}, {9, 10, 13, 14}], [40, {10}, {9, 13, 14}].

Table A.12: Results of large scale problems as $C_{\max}$ and e vary under 10 possible disruptions

d	$C_{\max}$	Unit outside option cost	Total cost	Outside option	Selected packages	Number of fortifications
700	2000	100	1184026.6	399250	32	1
		125	1264837.24	354190	38	1
		150	1334958	394170	38	1
		200	1461094	498550	39	1
		300	1708342	741090	40	1
		500	2192207	1206500	40	1
		1000	3398743	2413100	40	1
	5000	100	1174215	368480	32	3
		125	1248751	311670	38	3
		150	1309997	332910	39	3
		200	1415479	411860	40	3
		300	1618794	608400	40	3
		500	2014201	985390	40	3
		1000	2999590	1970800	40	3
	10000	100	1172946	346160	33	4
		125	1237693	272630	39	5
		150	1290988	294920	39	5
		200	1383119	357130	40	5
		300	1550265	494060	40	7
		500	1870949	800020	40	7
		1000	2669770	1597600	40	7
	15000	100	1172946	346160	33	4
		125	1237693	272630	39	5
		150	1290988	294920	39	5
		200	1383119	357130	40	5
		300	1546834	462830	40	10
		500	1855307	771090	40	10
		1000	2621431	1511800	40	10

The disrupted packages are assumed to be [5, {(7, 2), (17, 1), (18, 1), (32, 2), (40, 1)}, $(0.7, 0.9, 0.6, 0.4, 0.5)^T$], [8, {(7, 2), (8, 1), (8, 2), (16, 1), (17, 1), (18, 1), (32, 2), (40, 1)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.5, 0.6)^T$], [10, {(7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (32, 2), (40, 1)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5)^T$], [12, {(7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (32, 2), (39, 2), (40, 1), (40, 2)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5, 0.9, 0.7)^T$], [15, {(1, 2), (2, 2), (2, 3), (7, 2), (8, 1), (8, 2), (16, 1), (16, 2), (17, 1), (18, 1), (32, 1), (32, 2), (39, 2), (40, 1), (40, 2)}, $(0.8, 0.7, 0.5, 0.85, 0.6, 0.7, 0.9, 0.6, 0.4, 0.5, 0.9, 0.7, 0.6, 0.85, 0.5)^T$]. The number of winning 3PLs lies in [0, 40]. The protection cost of each 3PL for each package follows a uniform distribution on the support [1000, 4000]. The fixed transaction cost of relationship management cost of each 3PL follows a uniform distribution on the support [2000, 5000]. Other parameters are the same as the small scale problems.