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# Reliable container supply chain under disruption

Yoonjea Jeong<sup>1</sup> · Gwang Kim<sup>2</sup> · Ilkyeong Moon<sup>3,4</sup>

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## Abstract

In this study, we develop a reliable formulation based on a container network flow problem, along with the full implementation of an empty container management strategy in the context of an integer linear programming model. The proposed approach can play a key role in coping with disruption in the network and can offer a proactive measure for effective disruption management to maintain a stable level of reliability in supply capability. To formulate a reliable container network problem, we design the pattern of disruption, a rare and irregular uncertainty, based on binomial coefficients in the objective function. In this way, flow interruption due to disruption can be expressed in node- and arc-failures and can be properly managed. Furthermore, we provide a non-disruptive model based on a deterministic formulation derived from a bast-case scenario. Through numerical illustrations and sensitivity analyses, we conduct in-depth analyses on the impact of disruption in the container supply chain, and a benchmark model based on a bast-case scenario is used to determine disruption costs, for comparative study. In particular, the numerical experiments show that if both maritime and hinterland disruptions are not managed in advance, disruption costs derived from a benchmark model result in a significant surge according to increasing potential disruption risk. Throughout computational experiments, we also found that maritime disruption is more destructive to container supply capability than hinterland disruption is. In particular, critical findings show that when a certain level of threshold is violated, the proposed strategies are completely interrupted in a container supply chain. Therefore, proactive measures to keep up a reliability of container supply in a high-risk region are highly recommended for management side.

☑ Ilkyeong Moon ikmoon@snu.ac.kr

> Yoonjea Jeong yjeong88@dau.ac.kr

Gwang Kim gwangkim91@chosun.ac.kr

- <sup>1</sup> Department of Industrial and Management Systems Engineering, Dong-A University, Busan 49315, Korea
- <sup>2</sup> Division of Business Administration, Chosun University, Gwangju 61452, Korea
- <sup>3</sup> Department of Industrial Engineering, Seoul National University, Seoul 08826, Korea
- <sup>4</sup> Institute for Industrial Systems Innovation, Seoul National University, Seoul 08826, Korea

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# 1 Introduction

How to create an efficient container network model is a topic that has earned significant attention in maritime logistics literature, and the significance of relevant studies has increased from time to time. Nowadays, global shipping companies, such as ocean carriers, confront some serious challenges, or disruptions, in maritime logistics. These challenges triggered enormous surges in freight rates because of the interrupted flow of container movement. For example, Southeast Asian ports encountered threefold freight rates in late 2021 in comparison with the first half of the year, due to severe US port congestion that was caused in part by the booming market demand after the onset of the COVID-19 pandemic (Yeping, 2021). Specifically, the freight rate of a 40-foot-equivalent unit container reached up to 3000 US dollars in December 2021, compared to 1000 US dollars in the first half of 2021. Moreover, the German shipping liner, Hapag-Lloyd, reached more than a tenfold increase in net profits during the first nine months of 2021. The company reported that this drastic surge in revenue was generated by a rapid jump in average freight rates (Hapag-Lloyd Nine-Month Net Profit Soars 10-Fold on Record Freight Rates, 2021). The company's net profit rose to 5.6 billion euros in the first nine months of 2021, whereas 538 million euros were gained a year prior. Consequently, this unusual scenario implies severe infrastructure bottlenecks, mostly found in ports because of the coronavirus crisis that has disrupted the global container supply chain. According to UNCTAD calculations, Fig. 1 supports these statistics to show that the weekly Shanghai containerized freight index in main service routes reached the maximum level during the worst of the COVID-19 pandemic, compared to past years. This fact implies that supply chain disruption caused a significant increase in freight rates and led to an adverse impact on a sustainable supply chain across the globe (Anser et al., 2021).

In existing literature, the concept of sustainability in supply chain management has been used in a broad way with various definitions. The most traditional definition originates from



Fig. 1 Weekly Shanghai containerized freight index from 2009 to 2021 (UNCTAD Policy Brief, 2021)

the World Commission on Environmental and Development report issued by the United Nations in 1987. Specifically, the United Nations defined sustainable development as being the state in which the needs of the present are met without compromising the ability of the upcoming generation to satisfy their own needs (Lu et al., 2016). Therefore, we can consider economic and social needs, along with environmental needs, together (Lu et al., 2010). In opposition to the general concept of sustainability in supply chain management, Seuring and Müller (2008) pointed out some critical limitations within the relevant research area; that is, sustainability efforts are often limited to environmental improvements and frequently miss theoretical background in terms of overall sustainability in the supply chain. Moreover, critical perspective presents the research gap in the lack of quantitative model-based approaches (Brandenburg et al., 2014). In line with this claim, Lu et al. (2016) also stated that the main idea of sustainability should extend beyond environmental stewardship in port operations. In other words, designing a reliable container network in both hinterland and maritime regions necessitates an understanding of connections among economy, society, and the environment.

The contribution of this study to this interconnected framework of sustainability therefore touches on economic, societal, and environmental aspects. That is, this study proposes a reliable and robust container supply chain for a shipping company while taking into account all these angles. When disruption occurs, significant cost savings are incurred from having such a reliable design in place, compared to the non-disruptive model without disruption scenarios (see Fig. 2). In this regard, the sustainable supply of containers under the varying magnitude of disruptive forces should be taken into account as a potential risk. Overall, a shipping company can achieve a sustainable container supply chain, even under high uncertainty. Additionally, this study takes into account social factors, namely that consumers have already experienced a serious disruption in maritime logistics and supply chain during the COVID-19 pandemic. Many cities around the globe suffered shortages of necessities such as food, potable water, and energy, owing to complete shutdowns of ports. Thus, a sustainable supply of shipping containers plays a significant role in maintaining societal well-being, as well as in supporting social stability. Finally, this study also has an environmental angle. By taking into account smart ways to position empty containers during disruptions, the study proposes a more efficient way to preserve a certain level of reliability in supply capability. In this way, only the minimum repositioning frequency could satisfy the demands of a region where the deficit volume of empty containers is found. It is well known that a mega-sized container ship produces a significant amount of pollution in both hinterland and maritime regions, including CO<sub>2</sub> and GHG emissions. In this regard, the increasing frequency of empty container repositioning during disruptions not only causes operational and penalty costs derived through vessel delays but also has an adverse environmental impact. Even though some studies directly address sustainability in maritime logistics, most of them focus on vessel management for reducing  $CO_2$  and  $SO_x$  emissions, with the goal that vessel operators will consider environmental sustainability (Van den Berg & De Langen, 2017; Cheaitou & Cariou, 2019). In other words, such studies promote a decision-making system that is often confined to an operational level and a strictly environmental aspect, rather than a more broadly focused tactical level that ties in to other critical aspects, as our research attempts to do.

Nevertheless, most container network problems were developed based on deterministic formulations with fixed settings, including demands and lead times, to analyze their impact of key performance indicators on the basic container network structure. However, according to Qi (2015), two types of uncertainty were defined in container shipping networks, namely *recurring and regular*, or *rare and irregular uncertainties*. Compared to the former, the latter is extremely difficult to predict or even to put into a framework in which its pattern of



Fig. 2 Disruption scenario in a hinterland network for  $0 \le r \le |J|$ 

raw data can be estimated. This uncertainty is referred to as a *disruption*. Several types of disruption were found in a container network structure and comprehensively discussed by Kim et al. (2015). They showed that disruption and resilience in a supply network could be categorized from a network structural perspective; namely, *arc-*, *node-*, and *network-level* disruption. Any level completely blocks or partially interrupts flow arc capacities in different types of a supply network. For designing the pattern of disruption, we propose a theoretical background of a reliability-based formulation with expected terms expressed by the random failures of echelons in the objective function. More details of this modeling procedure are given in Sect. 4.

In this study, we assume that a container network is completely interrupted in nodelevel disruption, owing to any unexpected events, so that the corresponding arcs, including empty container repositioning and street-turn strategies, are no longer active. To maintain a certain level of reliability in the empty container supply, a shipping company prevents empty container stockouts for exporters in each region and supplies them with as many demands as possible. If demands are not met on time, shortage costs will be incurred. Therefore, the ultimate goal of a shipping company is to retain control of the entire container flow under a varying degree of disruption by adequately replying to the following research questions:

• How can we distribute a sufficient number of empty containers throughout each region during a disrupted container network?

- How can we achieve cost savings even when disruption extends throughout the entire network?
- How can we best implement an empty container management strategy under disruption?

To answer these questions, we have to design container shipping networks in a reliable and cost-efficient manner and examine the trade-off between normal and expected cost terms by comparing a benchmark model and by minimizing the expected total relevant costs in disruption scenarios, which are characterized by the numbers of nodes and arcs that have failed. To the best of our knowledge, our reliability-based approach is a novel contribution to the study of disruption management in the literature on container supply chains, in which the traditional approach deals with uncertainty in varying parameters—namely, a stochastic program. Snyder and Daskin (2005) claimed that this approach usually deals with an uncertain future condition and seeks demand-based robustness, while their approach seeks supplybased robustness in which parts of a system fail. In line with their work, we also seek reliability in supply capabilities for empty containers in a disrupted network, whereas most disruption management studies in maritime logistics focus mainly on vessel-related decisions. More important, the mechanism of our reliability-based model differs from that in work by them.

The structure of this study is organized as follows. In Sect. 2, we review existing literature. The problem statement is described in detail, and its mathematical model is given in Sect. 3. Thereafter, disruption used in this model is defined, and derivations of expected cost terms in our objective function are fully shown in Sect. 4. In Sect. 5, computational experiments, including sensitivity analyses on variations in key parameters, are conducted to offer managerial insights. The conclusion of this study is drawn in Sect. 6.

## 2 Literature review

The container shipping network problem has been extensively studied in existing literature and can be categorized by different empty container management (ECM) strategies. The ECR problem also has been extensively studied, with deterministic and stochastic perspectives. Shintani et al. (2007) designed a container shipping network for incorporating ECR activities and integrating two important decisions, including ship and container deployments. Kim et al. (2019) analyzed repositioning effects in hinterlands and the impact of using foldable containers at an operational level. They aggregated both shippers and consignees as a single customer node, including inland depots and seaports, and implicitly implemented a ST strategy with the top priority option. In this setup, customers were first served by empty containers that remained in their nodes and then satisfied the demands of subsequent customers. Furthermore, researchers have comprehensively employed state-of-the-art containers, or foldable containers, in the ECR problem to maximize savings of both money and space by developing a network flow model with aggregating demands at port areas (Myung, 2017; Myung & Moon, 2014; Wang et al., 2017). Lee et al. (2006) developed a multi-commodity network model based on a port-oriented network and analyzed the flow of containers in Asia-Pacific trade routes. They assumed a deterministic situation in which lead times between ports were known in advance.

In a stochastic framework, various types of ECR models were also developed based on uncertainty in key parameters. Di Francesco et al. (2009) proposed a time-extended multi-scenario optimization model in which each scenario was generated based on uncertain parameter types for solving the ECR problem. Erera et al. (2009) presented a robust optimization model for a dynamic ECR problem with uncertainty in forecasts of future supply and demand. This study also provided recovery actions with re-established feasibility in a given uncertainty set. Lee and Moon (2020) also solved a robust ECR problem with foldable containers under demand uncertainty via a robust optimization technique. They showed that their robust formulation could be harnessed as a tractable approximation of an intractable multistage stochastic program and proved a cost-saving effect by using foldable containers in computational experiments. Other uncertain data also have been considered in ECR literature. A two-stage stochastic program was developed by Long et al. (2012). Random demand, supply, ship weight, and space capacities all were taken into account in their model, while the sample average approximation method was used for a solution approach. To the best of our knowledge, another cost-efficient ECM strategy, ST, was not extensively studied, and yet we found few relevant papers that looked at this strategy. Deidda et al. (2008) studied the ST issue inherent in truck routes by applying a network design consisting of importers, exporters, and ports, along with an exact algorithm, while Furió et al. (2013) optimized empty container movements among shippers, consignees, terminals, and depots by using ST. Their proposed models were embedded in a decision support system, and they conducted case studies with real-world data from Valencia, Spain.

Unlike with the extensive ongoing research into disruption management (DM) in the airline industry, DM in the shipping liner industry recently has started to receive substantial attention in maritime logistics literature. Qi (2015) introduced several topics related to DM for vessel operations with port disruptions. Common methods for managing disruption in the recovery of containers involve speeding up vessels, skipping, and swapping a disrupted port (Abioye et al., 2019, 2020; Brouer et al., 2013; Li et al., 2016; Paul & Maloni, 2010). This research studied re-optimized or rescheduled ship routes whenever required. Disruption does not just cause uncertainty in ports, but also could impact vessels, due to disrupted transportation links. Similar studies into the berth allocation problem also found this to be true (Xu et al., 2012). Occasionally, such disruption might even prevent vessels from arriving on time at all ports so that an intentional delay is allowed, with some corresponding penalty costs, while restricting delays in a few key ports (Wang & Meng, 2012). These works simultaneously dealt with uncertainty and disruption at the operational level, but did not thoroughly deal with a tactical level of disruption that interrupts container network flows.

Although DM in container shipping networks has barely been written about in existing literature, DM in classic supply chain literature has already attracted a significant amount of attention from many researchers. Ivanov et al. (2017) comprehensively reviewed disruption recovery in supply chains and categorized papers based on different types of frameworks. Some reliability models for an uncapacitated facility location problem (UFLP) were proposed by Synder and Daskin (2005). They showed reliable solutions for the UFLP, in which a facility with less disruption costs would first be selected, even though optimal solutions from the UFLP would be improved with no disruption. In this way, reliable solutions would be cost-effective if disruption in a certain facility occurred. Cui et al. (2010) relaxed the assumption of homogenous disruption probabilities used in Daskin (2005), and applied sitedependent assumptions over disruption scenarios while using the continuum approximation model for sensitivity analysis. Berman et al. (2007) also studied reliability issues in facilities experiencing disruptions and showed that facilities in disrupted networks become more centralized and co-located when greater risks for disruption prevail. Overall, we share a similar philosophy with these works, but to implement ECM strategies, we concentrate our research on container supply chains that feature their own constraints. For example, instead of designating r as standing for closer facilities, we characterized r as the number of facilities that failed for every outcome of disruption scenarios in terms of arc- and node-failures.

Table 1 comprehensively summarizes several distinctive features of our model to highlight the contribution of this study to existing literature on the DM in shipping liners. First, this study presents a reliability-based model for both disruptive events, namely maritime and hinterland sides simultaneously, to provide the proactive DM, while most existing literature deals solely with maritime disruption from the perspective of reactive vessel management. In particular, a few papers handle decision-making in container management under disruption and do not comprehensively consider both disruptive events. For example, although Di Francesco et al. (2013) investigated disrupted container flows in a proactive manner, this work is limited to the ECR activities. Li et al. (2018) also examined the impact of disruption occurring in the hinterland for disruption response strategies in truck scheduling, and yet efforts in managing containers are restricted to the terminal side. Another contribution of this study can be found in the effective execution of various types of the ECM strategies when designing a reliable container network. To the best of our knowledge, facility failure by disruption is not extensively involved with the form of node- and arc-failures in the literature on container supply chains. Therefore, we proposed in our study the reliable container network flow model (RCNF) to minimize the expected total relevant cost under disruption while maintaining a certain level of reliability in empty supply capability without a significant increase in cost.

## 3 Problem description

In this section, we introduce the RCNF model that minimizes the total relevant cost composed of reusing and returning containers and the expected ST of containers, along with the corresponding arc failure costs and expected ECR costs, along with corresponding arc failure costs. Each shipper could be disrupted with a given identical probability, and multiple shippers may fail simultaneously. Another disruption occurs in repositioning arcs between ports with a given probability. In other words, the disruption we deal with in this study indicates a complete arc failure (a zero flow capacity in disrupted arcs). However, arcs between ports and shippers are set as infallible, because they are considered to be a basic function that serves customer demands in hinterland operations. ST failure may be attributed to various types of disruptions, such as disruptions in administration, natural disasters, traffic congestion, and other factors, while repositioning failure is frequently connected to port disruptions, such as failures by quay cranes in loading and unloading, operations that fail to reach their full capacity, or by complete system failures (Di Francesco et al., 2013). Other underlying assumptions are provided as follows:

- (i) Every hinterland operation, such as reusing, returning, and ST of containers, is completed within a single period, whereas ECR could take more than or equal to a single period, denoted by  $t_{pp'}$  (Jeong et al., 2018; Lee & Moon, 2020). Therefore, a single period indicates four days in this study.
- (ii) The specific destination of laden containers after serving demands for shippers is not taken into account to seek reduction in computational complexity. Furthermore, the focal interest of this study is to serve demand requests arising from empty container transportation (Lee & Moon, 2020).
- (iii) We relax a strict assumption that every container must be returned to a port after unpacking items from laden containers (Jeong et al., 2018; Song & Dong, 2012). In this study, consignees either become the suppliers of empty containers to shippers or return them to ports after use.

Table 1 Relevant Stu	udies related to	o disruption mar	nagement in ma	ritime logistics				
Author (year)	Measure type	ə	Disruptive ev	ent	Facility failure	Reliable design	Decision type	Solution methodology
	Reactive	Proactive	Maritime	Hinterland				
Paul and Maloni (2010)	>		>		>		Vessel	Simulation model
Wang and Meng (2012)	>	\$	>			`	Vessel	Mixed-integer nonlinear stochastic program
Brouer et al. (2013)	`		\$		`		Vessel	MIP
Francesco et al. (2013)		>	\$		`	`	Container	Muti-scenario model
Li et al. (2016)	`		>		`		Vessel	Multi-stage stochastic model
Fischer et al. (2016)	`	\$	`		`	`	Vessel	MIP
Xing and Zhong (2017)	`		>		`		Container	IP
Li et al. (2018)	>			>			Truck	Simulation model
Abioye et al. (2019)	`		>		`		Vessel	MINP
Abioye et al. (2020)	`		>		`		Vessel	MINP
Zeng et al. (2011)	`		>				Berth and quay crane	IP and tabu search
Li et al. (2015a, 2015b)	`		`		`		Vessel	NLP and DP algorithm
Xing and Wang (2019)	>		`				Vessel, container	MINLP

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Table 1 (continued	(							
Author (year)	Measure typ	e	Disruptive ev	/ent	Facility failure	Reliable design	Decision type	Solution methodology
	Reactive	Proactive	Maritime	Hinterland				
Lee et al (2015)		>	>			>	Vessel	Quantitative model
Kjeldsen et al. (2011)	`		>				Vessel, container	MIP
Gurning and Cahoon (2011)	`	`	>				Vessel	Markov chain process
Wide (2020a)	>			>			Hinterland transport	Case study
Wide (2020b)	`			>			Hinterland transport	Qualitative method
Loh and Thai (2015)		`	>	>			Truck, vessel	Simulation
Wu et al. (2019)		`	>				Vessel	Quantitative case study
Liu et al. (2022)	>		>	>			Vessel, container	MINP and AMPSO
This study		>	`	>	`	`	Container	Reliability-based IP

- (iv) All nodes are connected among consecutive echelons within the same region p and ports are also linked by ECR through a container supply chain alliance (Li et al., 2015a, 2015b). However, the repositioning of empty containers would not be allowed if disruption occurs with s.
- (v) The storage capacity of a port in each region is implicitly relaxed in this study because the minimization of inventory holding costs for empty containers at ports is one of the optimized objectives (Jeong et al., 2018).
- (vi) Every container is expressed in a twenty-foot unit (TEU).
- (vii) Container leasing is not explicitly considered, but shortage is allowed throughout the planning horizon T.
- (viii) Disruption probabilities, q and s, are site-independent.

For Assumption (i), the duration of maritime transportation exceeds that of hinterland operations, in practice. To integrate the different levels of decision-making, it is quite common to assume a single period for several days in most of the ECR literature; that is, Lee and Moon (2020) set a base period of four days to illustrate maritime transportation between inter- and intra-continental trade. To justify Assumption (ii), most of the ECR studies do not directly consider vessel routes, meaning that free empty container movement between any ports could be achieved for ECR. This also implies that laden container transportation is often ignored to focus instead on empty container movement. This study is also in line with the mainstream existing studies in this aspect. From Assumption (iii), we allow a cost-efficient ECM, the ST strategy, in this study. This strategy is now executed in practice and has started drawing significant attention in relevant research areas. In this regard, a shipping company is able to direct a consignee to deliver empty containers to a shipper in close proximity, instead of returning those containers to a port only (Deidda et al., 2008; Furió et al., 2013). The remaining assumptions are also pulled from existing container network literature.

To briefly explain the operation of normal container network flow, each shipper  $j \in J$  in region p has an empty container demand  $D_{jt}^p$  and each consignee  $i \in I$  can either supply or return empty containers  $L_{it}^p$  to j or to each port  $p \in P$  after use, respectively. Returned containers can be reused to serve  $D_{jt}^p$  during planning horizon T. Each shipper is assigned to a possible number of non-disruptive candidate suppliers and a port within the same region. If region p' significantly suffers from a shortage of empty containers against shippers, then the p region's surplus of empty containers could transport a proper repositioning quantity by transportation time  $t_{pp'}$ . Otherwise, the shipping company would not have any other options to satisfy demands, aside from leasing containers by  $b_p$ . In this study, we do not explicitly lease containers when shippers struggle with shortages within a certain period; rather, such a scenario is assumed to be a lost-sale opportunity,  $p_j$ . This cost could significantly vary, based on revenues that a shipping company could have earned for the travel distance to a destination in which shippers send their shipments after packing empty containers.

The notation used for the RCNF model is summarized in Tables 2 and 3. Sets for each echelon are considered as nodes in a container network, along with multi-periods. Relevant cost parameters, including repositioning and hinterland transportation costs, storage costs, and penalty costs, would be randomly generated, as would supply and demand. To design a reliable container network flow, arc variables for ECM strategies are required, along with indicator variables for storage.

With the given notations, we develop a mathematical model based on a container network flow by using normal and expected cost terms in the objective function and the corresponding constraints by characterizing a container network flow.

Minimize  $E[TRC] = normal \ costs + expected \ costs$ 

#### Table 2 Sets and parameters

Model paran	neters
I	Set of consignees
J	Set of shippers
Т	Set of periods
Р	Set of ports
$c_{pj}$	Inland transportation cost from port p to shipper j
$c_{ij}^p$	Inland transportation cost directly from consignee i to shipper j within region of port p
$c_{ip}$	Inland transportation cost from consignee i to port p
$c_{pp'}$	Repositioning cost from port p to another port p'
$h_p$	Storage cost at port p
$p_j$	Penalty cost payable to shipper j by shipping company in region of port p
$D_{jt}^p$	Demand of empty containers for shipper j in period t within region of port p
$L_{it}^p$	Supply of laden containers from consignee i in period t within region of port p after use
INV <sub>p</sub>	Initial inventory of empty containers at port p
$b_p$	Failure cost for street turn and repositioning based on leasing activity within region of port p
$t_{pp'}$	Vessel transportation time from port p to port $p'$
q	Disruption probability for street-turn $(0 < q < 1)$
S	Disruption probability for repositioning $(0 < s < 1)$

Integer variables	
<i>q<sub>pjt</sub></i>	Number of empty containers transported from port p to shipper j in period t
$y_{ijt}^p$	Number of empty containers directly transported from consignee i to shipper j in period t within region of port p
<i>z<sub>ipt</sub></i>	Number of empty containers transported from consignee i to port p in period t after use
$r_{pp't}$	Number of repositioned containers from port p to another port p in period t
$IE_t^p$	Number of empty containers stored at port p in period t
$\delta^{p}_{jt}$	Level of shortage for shipper j in period t at region of port p

where normal  $\cos ts = reusing + returning + storage + shortage costs$ expected  $\cos ts = street turn + ERC + failure$ 

$$IE_{1}^{p} = INV_{p} + \sum_{i \in I} z_{ipt} - \sum_{j \in J} q_{pjt} - \sum_{p' \in P, p' \neq p, t+t_{pp'} \leq T} r_{pp't}, \forall p \in P$$
(1)  
$$IE_{t}^{p} = IE_{t-1}^{p} + \sum_{i \in I} z_{ipt} - \sum_{j \in J} q_{pjt} - \sum_{p' \in P, p' \neq p, t+t_{pp'} \leq T} r_{pp't}$$

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$$+\sum_{p'\in P, p'\neq p, t>gt; t_{pp'}} r_{p'p, \left(t-t_{p'p}\right)}, \forall t = 2, \cdots, |T|, p \in P$$
(2)

$$y_{ijt}^{p} \le L_{it}^{p}, \forall i \in I, j \in J, t \in T, p \in P$$
(3)

$$\sum_{i \in I} y_{ijt}^p + q_{pjt} \le D_{jt}^p, \forall j \in J, t \in T, p \in P$$

$$\tag{4}$$

$$\delta_{jt}^{p} = D_{jt}^{p} - \left(\sum_{i \in I} y_{ijt}^{p} + q_{pjt}\right), \forall j \in J, p \in P, t \in T$$

$$(5)$$

$$L_{it}^p - \sum_{j \in J} y_{ijt}^p = z_{ipt}, \forall i \in I, p \in P, t \in T$$
(6)

$$q_{pjt}, y_{ijt}^{p}, z_{ipt}, \delta_{jt}^{p}, r_{pp't}, IE_{t}^{p} \in z_{+}, \forall i \in I, j \in J, p \in P, p' \in P, t \in T$$
(7)

The objective function of the RCNF model includes several ECM cost terms including shortages to characterize disruption-related costs, and ECR and ST costs are described as expected terms to characterize the impact of disruption in supply reliability as well as failure costs. The detailed illustration for deriving the objective function will be given in Sect. 4.2. Constraints (1) and (2) represent the number of empty containers stored at port *p* for each period. This inventory in period *t* depends on the inventory level from the previous period *t*-1 and the number of empty containers to be repositioned from port *p* in period *t* which will arrive at port p' after  $t + t_{pp'}$ . Constraint (3) represents the maximum supply capacity for ST, which is equivalent to the number of laden containers received by the consignee *i*. Constraints (4) and (5) together ensure the demand fulfillment for shippers either from multiple consignees or from a port within the same region, and allow for the shortage of demand by shippers. Given the nature of the minimization problem, one would strive to incur fewer shortages unless supply capacity from consignees and ports becomes completely absent for a particular period. If full supply capacity is not utilized for ST, empty container leftovers would be returned to port *p*. Constraint (7) shows non-negativity and integer decisions.

## 4 Reliability model under disruption

In this section, we characterize the pattern of disruption that occurred in ST and ERC implementation. Although we defined that disruption is hardly predictable for estimating its pattern, q and s may be assessed based on historical data such as weather-related disruption. However, they should be subjectively assessed for disruption caused by manmade disruption (i.e., labor strike or malfunction). Most importantly, disruption is statistically independent from facility to facility and from region to region as shown in Assumption (viii) (Snyder & Shen, 2019). Hence, we also assume that q and s follow a two-state Markov process.

#### 4.1 Designing the patterns of q and s

Each ST arc (i, j) has the identical probability, q, of disruption, resulting in arc failure to implement ST between consignee i and shipper j. Figure 2 illustrates the possible disruption scenario of ST implementation. Let r be the number of nodes failed; that is, all or none of the arcs stay connected. Suppose |I| = |J| = 3. When r = 0 or 3, only a single disruption scenario is plausible; that is, the network is either fully connected or disconnected, respectively. When  $1 \le r < |J|$ , multiple outcomes could be generated based on the size of

|J|. Under this illustration, three possible outcomes are generated for r = 1 and 2. Therefore, depending on the size of r, the probability of each disruption scenario is generalized with  $q^r(1-q)^{|J|-r}$ . In other words,  $(1-q)^{|J|-r}$  indicates the number of open facilities, |J|-r, while  $q^r$  shows the number of facilities failed, r, as defined in the notations. In this way, we discovered some critical aspects of designing the pattern of q.

Similarly, each repositioning arc (p, p') also has the identical probability *s* of disruption, resulting in another arc failure between the responsible ports. Unlike hinterland operations, maritime transportation takes  $t_{pp'}$ . We assume that the inflow of repositioning empty containers is disrupted in each period and that the corresponding arc fails. In this sense, one can generalize the probability of a disruption scenario in seaborne routes with  $s'(1-s)^{|P|-1-r}$ . Unlike ST disruption, the number of maritime disruptions may affect container flow in the network even more adversely, due to significant reductions in supply capacities at ports.

Even though disruption seems rare and irregular to approximately estimate certain patterns due to high randomness, this figure reveals that the number of possible outcomes stemming from a disruption scenario based on facility failures follows the binomial pattern. Hence, some modeling techniques for the objective function could be used to involve this disruption scenario in designing the reliable container network, and the strategic DM on the network could be executed in a proactive manner. Furthermore, a decision maker in a shipping company can analyze the impact of disruption on their regular or irregular service routes in terms of container flow management. To effectively explain the main idea of this design, we will analyze the following illustrative example, which is represented in the simple problem instance size.

**Example 1** Suppose, for this example, a container shipping network with |I| = |J| = |P| = |T| = 3, and suppose that shipping costs between *i* and *j* depend on their distances, and the hinterland transportation costs from or to *p* are higher than ST costs, because ports are usually located relatively farther apart than their customers are. Figure 3 illustrates that each network is designed based on the non-disruptive and the RCNF models, and we will show



Fig. 3 a optimal solutions (left); and b reliable solutions (right) for Example 1

how the RCNF model could be effective in terms of cost-saving and reliability under a disruption scenario. If Shipper 3 is disrupted in the non-disruptive model (r = 1), an additional cost for disrupted arcs (2, 3) and (1, 3) would be \$480 \* (23 + 7) = \$14, 400, whereas an additional cost in the RCNF is \$480 \* 8 = \$3, 840 for leasing activities used as a penalty, so that the non-disruptive model bears an additional cost of \$10, 560(\$14, 400 - \$3, 840). Note that (p, 3) in both models is assumed to be non-failed in this study. In contrast, when no disruption occurs in either model, the RCNF model bears an additional cost of \$5, 970(\$150 \* 23 + \$120 \* 7 - \$120 \* 8 - \$250 \* 38) to satisfy the demand of Shipper 3 by using a cost-inefficient route (p, 3). Overall, the non-disruptive and the RCNF models incurred costs of \$20, 170 and \$23, 070 for Period 3. This example indicates that reliable solutions could maintain a similar level of reliability without significant increases in costs, compared to optimal solutions.

## 4.2 Objective function

The RCNF model minimizes normal operation costs, including reusing, returning, storage, shortage, and expected transportation costs, as well as ST and ECR. By using Fig. 2, the following proposition could be provided.

**Proposition 1** If arcs (i, j) and (p, p') are assumed to have potential node- and arc-failures with site-independent disruption probabilities (Assumption (viii)), 0 < q < 1 and 0 < s < 1, the expected cost terms follow the binomial coefficients for every r.

For the proof of Proposition 1, we will show how to derive the expected ST and repositioning costs, along with the corresponding failure costs. Please note that this derivation follows in the same manner from Fig. 2 and is represented in a rigorous mathematical modeling aspect. To effectively show the binomial pattern, suppose |I| = |J| = 5 for all t and p. The ST cost terms can be represented in a tableau form with extended equations as follows:

$$\sum_{t \in T} \sum_{i=1}^{5} \sum_{j=1}^{5} c_{ij}^{p} y_{ijt}^{p} \approx \begin{pmatrix} A_{1} & A_{2} & A_{3} & A_{4} & A_{5} \\ \overline{c_{11}^{p} y_{11t}^{p}} + \overline{c_{12}^{p} y_{12t}^{p}} + \overline{c_{13}^{p} y_{13t}^{p}} + \overline{c_{14}^{p} y_{14t}^{p}} + \overline{c_{15}^{p} y_{15t}^{p}} + \\ c_{21}^{p} y_{21t}^{p} + c_{22}^{p} y_{22t}^{p} + c_{23}^{p} y_{23t}^{p} + c_{24}^{p} y_{24t}^{p} + c_{25}^{p} y_{25t}^{p} + \\ c_{31}^{p} y_{31t}^{p} + c_{32}^{p} y_{32t}^{p} + c_{33}^{p} y_{33t}^{p} + c_{34}^{p} y_{34t}^{p} + c_{45}^{p} y_{35t}^{p} + \\ c_{41}^{p} y_{41t}^{p} + c_{42}^{p} y_{42t}^{p} + c_{43}^{p} y_{43t}^{p} + c_{44}^{p} y_{44t}^{p} + c_{45}^{p} y_{45t}^{p} + \\ c_{51}^{p} y_{51t}^{p} + c_{52}^{p} y_{52t}^{p} + c_{53}^{p} y_{53t}^{p} + c_{54}^{p} y_{54t}^{p} + c_{55}^{p} y_{55t}^{p} \end{pmatrix}$$
(8)

For better representation, let  $A_i$  for  $i = 1, \dots, 5$  be the  $i^{th}$  column of Eq. (8) as shown above. This equation is properly reorganized into a tableau form. Please also note that  $A_1 = c_{11}^p y_{11t}^p + \dots + c_{51}^p y_{51t}^p$ , and the remaining  $A_i$  for  $i = 2, \dots, 5$  have the ST cost components in a similar way. When nodes between the consecutive echelons are fully connected (r = 0), the following expected cost term is shown in a simplified form with disruption probability q:

$$E\left[\sum_{i=1}^{5} A_i | r = 0\right] = 1 \cdot (1-q)^5 (A_1 + A_2 + A_3 + A_4 + A_5)$$

As shown in Fig. 2, multiple outcomes of a disruption scenario could be obtained for  $1 \le r < |J|-1$ ,  $\forall r \in Z_+$ . Equation (9) represents r = 1, and each zero shows facility failure. For example, the first row of Eq. (9) has  $A_5 = 0$ , meaning that  $y_{15t}^p = y_{25t}^p = \cdots y_{55t}^p = 0$ . This representation indicates all ST arcs from  $i = 1, \dots, 5$  to j = 5 experience failure at Consignee 5, resulting in completely interrupted empty supply to other shippers. In this manner, five possible outcomes, differing from each individual facility failure, are taken into account for r = 1, and the common coefficient of Equation(9) can be derived as follows:

$$E\left[\sum_{i=1}^{5} A_{i}|r=1\right] = q^{1}(1-q)^{4} \begin{pmatrix} A_{1} A_{2} A_{3} A_{4} & 0 \\ + & + & + & + \\ A_{1} A_{2} A_{3} & 0 & A_{5} \\ + & + & + & + \\ A_{1} A_{2} & 0 & A_{4} A_{5} \\ + & + & + & + \\ A_{1} & 0 & A_{3} A_{4} A_{5} \\ + & + & + & + \\ 0 & A_{2} A_{3} A_{4} A_{5} \end{pmatrix}$$
$$\approx q^{1}(1-q)^{4}[4A_{1} + 4A_{2} + 4A_{3} + 4A_{4} + 4A_{5}]$$
$$= 4 \cdot q^{1}(1-q)^{4}[A_{1} + A_{2} + A_{3} + A_{4} + A_{5}] \tag{9}$$

It is noted that each row of the matrix indicates a possible disruption scenario with a single facility failure, resulting in every arc being disconnected from a shipper *j*, by multiple consignees *i*. For r = 2, ten possible disruption scenarios are generated with the given probability in Eq. (10).

$$E\left[\sum_{i=1}^{5} A_{i}|r=2\right] = q^{2}(1-q)^{3} \begin{pmatrix} A_{1} A_{2} A_{3} & 0 & 0\\ A_{1} A_{2} & 0 & 0 & A_{5}\\ A_{1} & 0 & 0 & A_{4} & A_{4}\\ 0 & 0 & A_{3} & A_{4} & A_{5}\\ 0 & A_{2} & A_{3} & A_{4} & 0\\ 0 & A_{2} & A_{3} & 0 & A_{5}\\ A_{1} & A_{2} & 0 & A_{4} & 0\\ A_{1} & 0 & A_{3} & A_{4} & 0\\ A_{1} & 0 & A_{3} & 0 & A_{5}\\ 0 & A_{2} & 0 & A_{4} & A_{5} \end{pmatrix} \\ \approx 6 \cdot q^{2}(1-q)^{3}[A_{1} + A_{2} + A_{3} + A_{4} + A_{5}]$$
(10)

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For r = 3, Eq. (10) has the value of common coefficient, 4.

$$E\left[\sum_{i=1}^{5} A_{i}|r=3\right] = q^{2}(1-q)^{3} \begin{pmatrix} A_{1} A_{2} & 0 & 0 & 0 \\ A_{1} & 0 & A_{3} & 0 & 0 \\ A_{1} & 0 & 0 & A_{4} & 0 \\ A_{1} & 0 & 0 & 0 & A_{5} \\ 0 & A_{2} & A_{3} & 0 & 0 \\ 0 & A_{2} & 0 & A_{4} & 0 \\ 0 & A_{2} & 0 & 0 & A_{5} \\ 0 & 0 & A_{3} & 0 & A_{5} \\ 0 & 0 & 0 & A_{4} & A_{5} \end{pmatrix}$$
(11)

$$\approx 4 \cdot q^{3} (1-q)^{2} (A_{1} + A_{2} + A_{3} + A_{4} + A_{5})$$

Finally, the common coefficient of Eq. (11) is computed.

$$E\left[\sum_{i=1}^{5} A_{i}|r=4\right] = q^{2}(1-q)^{3} \begin{pmatrix} A_{1} & 0 & 0 & 0 \\ 0 & A_{2} & 0 & 0 & 0 \\ 0 & 0 & A_{3} & 0 & 0 \\ 0 & 0 & 0 & A_{4} & 0 \\ 0 & 0 & 0 & 0 & A_{5} \end{pmatrix} \approx 1 \cdot q^{4}(1-q)^{1}(A_{1}+A_{2}+A_{3}+A_{4}+A_{5})$$
(12)

It is noted that one does not even have to consider r = 5, because all of the elements become zero in the matrix of  $A_i$ . For instance, (0 + 0 + 0 + 0 + 0). By observing consistent changes in patterns for common coefficients through Eqs. (9)–(11) one can easily see that they follow a binomial coefficient, as shown below.

$$\left\{C_r^{|J|-1}| for all integers r: 0 \le r \le |J|-1: |J|=5\right\} = \left\{\binom{4}{0}, \binom{4}{1}, \binom{4}{2}, \binom{4}{3}, \binom{4}{4}\right\}$$

Following all given steps, one can generalize the expected ST cost term for each region of Port p and period t as shown.

$$E\left[\sum_{i=1}^{|J|} A_i | 0 \le r \le |J| - 1\right] = \sum_{r=0}^{|J|-1} C_r^{|J|-1} \cdot q^r (1-q)^{(|J|-r)} \sum_{i=1}^{|J|} A_i$$

For  $r \ge 1$ , arc failure costs also should be taken into account, denoted by  $b_p$  and it is assumed that reusing arc (p, j) experiences non-failure. When every ST arc (i, j) is disrupted and port p suffers from a severe shortage of empty containers, a shipping company has only the sole option of leasing deficit containers. Hence,  $b_p$  is levied based on a unit cost of leasing. Because we do not explicitly lease containers in this study, expected failure costs are supplemented along with expected ST costs. To do so, we will use the same example of deriving the expected ST costs. Denote  $A'_i$  for  $i = 1, \dots, 5$  is the *i*.<sup>th</sup> column of A' for expected failure costs. For simplification, we transform the extended equations of the ECR cost terms in Eq. (12)

$$E\left[\sum_{i=1}^{5} A_{i}^{'}|r=1\right] = q^{1}(1-q)^{4} \begin{pmatrix} 0 & 0 & 0 & 0 & A_{5}^{'} \\ 0 & 0 & 0 & A_{4}^{'} & 0 \\ 0 & 0 & A_{3}^{'} & 0 & 0 \\ 0 & A_{2}^{'} & 0 & 0 & 0 \\ A_{1}^{'} & 0 & 0 & 0 & 0 \end{pmatrix} \approx 1 \cdot q^{1}(1-q)^{4} \left[A_{1}^{'} + A_{2}^{'} + A_{3}^{'} + A_{4}^{'} + A_{5}^{'}\right]$$
(13)

This highlights that  $A'_i$  is a complement of  $A_i$ . We can easily derive the coefficients of  $A'_i$  by using a similar procedure for  $1 \le r \le |J|$ . Unlike the upper bound of the expected ST costs, represented by |J| - 1, complete failure, up to |J|, should be taken into account for the upper bound of *r*. Hence, the common coefficients of  $A'_i$  could be obtained by using a total combination of possible outcomes. In addition, using recursive formula for the binomial coefficient,  $C_r^{|J|} - C_r^{|J|-1} = C_{r-1}^{|J|-1}$  is satisfied.

$$\left\{C_{r-1}^{|J|-1}| for all integers r: 1 \le r \le |J|\right\}$$

Therefore, the expected failure cost term against ST is derived as follows:

$$E\left[\sum_{i=1}^{|J|} A_i' | 1 \le r \le |J|\right] = \sum_{r=1}^{|J|} C_{r-1}^{|J|-1} \cdot q^r (1-q)^{(|J|-r)} \sum_{i=1}^{|J|} A_i'$$

The repositioning of arc (p, p') can be disrupted in a similar way to ST in the hinterlands. However, empty containers should be repositioned from one port to another port where empty containers are in high demand. For p = p',  $r_{pp't} = 0$ ,  $\forall t$  because the ECR transportation does not occur within the same port. In light of this constraint, the repositioning cost term can be presented as a tableau form in Eq. (13):

$$\sum_{t \in T} \sum_{p=1}^{5} \sum_{p'=1, p \neq p'}^{5} c_{pp'} r_{pp't} \approx \begin{pmatrix} 0 & c_{12}r_{12t} & c_{13}r_{13t} & c_{14}r_{14t} & \overline{c_{15}r_{15t}} \\ c_{21}r_{21t} & 0 & c_{23}r_{23t} & c_{24}r_{24t} & c_{25}r_{25t} \\ c_{31}r_{31t} & c_{32}r_{32t} & 0 & c_{34}r_{34t} & c_{35}r_{35t} \\ c_{41}r_{41t} & c_{42}r_{42t} & c_{43}r_{43t} & 0 & c_{45}r_{45t} \\ \overline{B_1} & \overline{B_2} & \overline{B_3} & \overline{B_4} & 0 \end{pmatrix}$$
(14)

It is noted that we do not reposition empty containers from the port of origin to the same port. By using a substitute,  $B_i$  for  $i = 1, \dots, 5$ , common coefficients are achieved in an analogous manner from expected ST costs, and the expected repositioning costs are derived with a repositioning disruption probability, *s*, as follows:

$$E\left[\sum_{i=1}^{|P|} B_i | 0 \le r \le |P| - 1\right] = \sum_{r=0}^{|P|-1} C_r^{|P|-1} s^r \cdot (1-s)^{(|P|-1-r)} \sum_{i=1}^{|P|} B_i$$

It is noted that the undisruptive probability,  $(1 - s)^{(|P|-1-r)}$ , shows that a port must reposition empty containers to another port, excluding the origin of departure port. Likewise, the expected failure cost of repositioning can be shown by using a complement of  $B_i$ ,  $B'_i$ . In

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addition, using recursive formula for the binomial coefficient,  $C_r^{|P|} - C_r^{|P|-1} = C_{r-1}^{|P|-1}$  is satisfied.

$$E\left[\sum_{i=1}^{|P|} B'_i | 1 \le r \le |P|\right] = \sum_{r=1}^{|P|} C_{r-1}^{|P|-1} \cdot s^r (1-s)^{(|P|-1-r)} \sum_{i=1}^{|P|} B'_i$$

In the end, our objective function involves undisruptive operation costs, including reusing, returning, storage, shortage, and disruptive operation costs comprising ST and ECR, represented by expected values. Our expected total relevant costs cover most of the ECM in the RCNF model.

The binomial coefficients from Proposition 1 can be also transformed into an extended version by using factorial terms.

#### MinimizeE[TRC]

$$subjectto(1) \cdots (7)$$

where 
$$E[TRC] = \sum_{p \in P} \sum_{j \in J} \sum_{t \in T} c_{pj}q_{pjt}$$
  
 $+ \sum_{r=0}^{|J|-1} \frac{(|J|-1)!}{r!(|J|-1-r)!} q^r (1-q)^{(|J|-r)} \left[ \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} c_{ij}^p y_{ijt}^p \right]$   
 $+ \sum_{r=1}^{|J|} \frac{(|J|-1)!}{(r-1)!(|J|-r)!} q^r (1-q)^{(|J|-r)} \left[ \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} b_p y_{ijt}^p \right]$   
 $+ \sum_{i \in I} \sum_{p \in P} \sum_{t \in T} c_{ip} z_{ipt}$   
 $+ \sum_{r=0}^{|P|-1} \frac{(|P|-1)!}{r!(|P|-1-r)!} s^r (1-s)^{(|P|-1-r)} \left[ \sum_{p \in P} \sum_{p' \in P} \sum_{t \in T} c_{pp'} r_{pp't} \right]$   
 $+ \sum_{r=1}^{|P|} \frac{(|P|-1)!}{(r-1)!(|P|-r)!} s^r (1-s)^{(|P|-1-r)} \left[ \sum_{p \in P} \sum_{p' \in P} \sum_{t \in T} b_p r_{pp't} \right]$   
 $+ \sum_{p \in P} \sum_{t \in T} h_p I E_t^p + \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} p_j \delta_{jt}^p$ 

## 5 Computational experiments

We carried out a series of numerical experiments of different values of disruption probabilities, *s* and *q*, to evaluate the impact of each disruption scenario for the RCNF problem by comparing solutions for the *non-disruptive model*. For the objective function of this model, expected ST and ECR costs are relaxed to deterministic costs, as shown below.

MinimizeT RC

$$subjectto(1) \cdots (7)$$

where TRC = 
$$\sum_{p \in P} \sum_{j \in J} \sum_{t \in T} c_{pj} q_{pjt} + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} c_{ij}^{p} y_{ijt}^{p}$$
$$+ \sum_{i \in I} \sum_{p \in P} \sum_{t \in T} c_{ip} z_{ipt} + \sum_{p \in P} \sum_{p' \in P} \sum_{t \in T} c_{pp'} r_{pp't}$$
$$+ \sum_{p \in P} \sum_{t \in T} h_{p} I E_{t}^{p} + \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} p_{j} \delta_{jt}^{p}$$

With this deterministic objective function and the corresponding constraints, the best-case scenario driven by this model can be used to compute disruption costs (in percentages) by using the gap between objective values from the RCNF model,  $Z_{RCNF}$ , and the best-case scenario,  $Z_{Best}$ , respectively. In this way, one can estimate the scale of potential disruption costs and use them as a benchmark model for each disruption scenario.

$$\operatorname{Gap}\left(\%\right) = \frac{Z_{RCNF} - Z_{Best}}{Z_{Best}} \times 100$$

To verify the proposed model, we tested 16 instances with varying *s* and *q* to investigate the impact of these values on disruption costs, where  $s, q \in \{0.05, 0.35, 0.65, 0.95\}$ . For the general experimental settings, the following set parameters were given: |I| = |J| = |T| = 50; |P| = 10. Each period represented four days. In this sense, the entire planning horizon indicates annual operation in a container shipping network. In Table 4, cost, demand, and supply parameters are randomly generated by following uniform distribution. They are imported from works by Jeong et al. (2018) and Moon and Hong (2016) and adjusted to our model accordingly. We also separated *import-* and *export-oriented* regions by assigning transportation time,  $t_{pp'} = 4$ ; namely, regions  $p = 1, \dots, 5$  have a deficit of empty containers, and regions  $p = 6, \dots, 10$  have a surplus by assigning different levels of demand and supply. In this way, we can emulate the imbalance of empty containers between inter-continental trade routes. To ensure an objective performance evaluation, all computational experiments were conducted with an Intel core<sup>TM</sup> i3-4160 computer with 3.60 GHz processors and 4.00 GB RAM.

It is observed that disruption costs in terms of the gap (percentage) between  $Z_{RCNF}$ and  $Z_{Best}$  both significantly increased when degrees of s and q consistently rose in Table 5. Especially for s = 0.95, disruption costs surged, compared to other values of s. This implies that disruption costs are far more sensitive to failure in ECR than to failure in ST. In other words, it would be more hazardous to plan for positioning a higher quantity of empty containers under the imbalance of empty containers scenario. Furthermore, for q = 0.95under any s setup, it was found that there was a far lower quantity of ST situations and a higher quantity of situations involving reuse and return of empty containers. It was noted, then,

<b>Table 4</b> Cost, demand, and supply           parameters	Returning cost in \$/unit	U (200,300)
	Street-turn cost in \$/unit	U (100,300)
	Reusing cost in \$/unit	U (200,300)
	Initial inventory level of port p in \$/unit	U (150,200)
	Storage cost of port p in \$/unit	U (50,70)
	Penalty cost in \$/unit	U (300,450)
	Failure cost in \$/unit	U (470,490)
	Demand for shipper <i>j</i>	U (5,15)
	Supply from consignee <i>i</i>	U (1,11)

s	q	$Z_{RCNF}($ \$)	$Z_{Best}($ \$)	Gap (%)
0.05	0.05	111,387,581	107,445,453	3.67
	0.35	128,073,161		19.20
	0.65	144,741,248		34.71
	0.95	161,157,773		49.99
Average	-	-	-	26.89
0.35	0.05	122,091,582	107,445,453	13.63
	0.35	138,777,167		29.16
	0.65	155,445,257		44.67
	0.95	171,861,840		59.95
Average	-	-	-	36.85
0.65	0.05	151,104,502	107,445,453	40.63
	0.35	167,789,989		56.16
	0.65	184,457,895		71.68
	0.95	200,874,283		86.95
Average	-	-	-	63.86
0.95	0.05	528,112,171	107,445,453	391.52
	0.35	544,797,657		407.05
	0.65	561,465,563		422.56
	0.95	577,881,951		437.84
Average	-	-	-	417.74

Table 5 Results of RCNF and non-disruptive models

that ST is a cost-efficient practice because it only requires a single unit cost,  $c_{ij}^p$ , compared to the container reuse setup,  $c_{ip} + c_{pj}$ , to serve any  $D_{jt}^p$ . However, optimal solutions in the test instances showed significant variation, while expected total relevant costs increased in a great number of test instances. Therefore, we will provide an in-depth analysis on reliability in optimal solutions in the next sensitivity analysis.

# 5.1 Effect of expected failure costs

Let us now consider |I| = |J| = 30, |T| = 20; |P| = 10,  $b_p \sim U(1400, 1500)$ , and more variation between  $D_{jt}^p$  and  $L_{it}^p$  for triggering more ECR activities during the planning horizon. Figure 4 shows variation in the total numbers of empty containers used by ST, reusing, and returning, and expected ST and failure costs for s = 0.45. Prior to s < 0.45 and q < 0.20, optimal solutions are almost insensitive to change in *s* and *q*, and thereafter keep varying until s = 0.60 and q = 0.40. Moreover, values of optimal solutions in the non-disruptive model do not greatly differ from those of the RCNF model before 0.45 and q < 0.20. Hence, we concluded that the model is reluctant to change to reliable solutions until passing some thresholds of *s* and *q*; that is, it requires a certain amount of expected failure costs impacting optimal solutions, as illustrated in the left of Fig. 4. It is better for shipping companies to rely less on ST situations and more on reuse of empty containers, along with other returning scenarios, but in doing so companies might be burdened with additional disruption costs,



**Fig. 4** Expected ST and failure costs with  $y_{ijt}^{p}^{*}$ ,  $q_{pjt}^{*}$ , and  $z_{ipt}^{*}$  when s = 0.45

compared to the minimum total costs achieved by using the non-disruptive model. Incurring such costs would not be worth the investment in the absence of disruption, but instead would help to maintain reliability in the supply of empty containers while incurring relatively low expected total relevant costs in the event of disruptions. In the end, relying on the ST would not be useful at all for q > 0.40.

In fixing s = 0.20, we also conducted a sensitivity analysis on increasing q. We conducted this analysis to explore the impact on expected ST and failure costs, repositioning costs, storage costs, and shortage costs, as shown in Fig. 5. It is clearly observed from this figure that a substantial increase in storage was found when repositioning activities decreased to almost zero for s > 0.55 to preserve reliability in the container network flow. In this experiment, repositioning empty containers directly resulted in an increase in shortages. Therefore, container flow is more adversely affected by repositioning more containers within ports, where a high possibility of disruption is often detected, to facilitate empty container flow within a container shipping network. In addition, when both ST and repositioning quantities dropped to zero, no further change in optimal solutions was made.



**Fig. 5** Expected repositioning and failure costs with  $r_{pp't}^{p}$ ,  $IE_t^{p}$ , and  $\delta_{jt}^{p}$  when q = 0.20

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## 5.2 Effect of different network structures

Another sensitivity analysis was conducted to investigate the effect of the varying numbers of I and J and to discover the trend of key performance measures. Two typical network structures are introduced for this analysis; namely, *consignee-oriented* and *shipper-oriented* network structures. The former one is frequently found in import-oriented nations such as North America and Western Europe, whereas the latter one represents export-oriented nations such as Far East Asia. Hence, the number of consignees dominates that of shippers in the former network, and vice versa. We fixed q = 0.30 and s = 0.50 where reliable solutions were found compared to those of the non-disruptive model, and we created 10 datasets based on the number of each echelon in Table 6. Most of the cost parameters follow Table 4, but  $D_{jt}^p$  and  $L_{it}^p$  follow U(5, 15) and U(0, 10) to show the imbalance of empty containers in demand and supply, respectively.

Figure 6 indicates disruption costs in terms of gaps in percentages when they are compared to those of the non-disruptive model, and an opposite trend was demonstrated when both sizes of datasets increased by five. This gap is attributable to the sizes of  $D_{jt}^p$  and  $L_{it}^p$ , due to the different number of nodes. However, an evident pattern of change in each node was produced; that is, although disruption costs for a consignee-oriented network nodes were very high in comparison to the shipper-oriented scenario, they continuously decreased as the node size increased. On the other hand, despite low disruption costs, these costs from shipper-oriented dataset tended to increase. Hence, higher disruption costs would be a burden in an imbalanced network structure, |I| < |J|, and vice versa. This implication shows that such a network is either vulnerable to disruption or prevents disruption, especially in the ST strategy.

Using the same datasets from Table 4, we calculated the implementation of key ECM strategies in a similar way to that in which we calculated gaps for disruption costs to verify certain trends for imbalanced networks (see Fig. 7). Please note that disrupted utilization indicates usage ratios of reliable and optimal solutions, generated by the RCNF and non-disruptive models. For ST utilization,  $y_{\text{BEST}}^*$  and  $y_{\text{RCNF}}^*$  represent optimal and reliable solutions, respectively, as well as  $r_{\text{BEST}}^*$  and  $r_{\text{RCNF}}^*$ , as follows:

disrupted utilization for 
$$ST = \frac{(y_{\text{BEST}}^* - y_{\text{RCNF}}^*)}{y_{\text{BEST}}^*} \times 100$$

Consignee-oriented 1 30 5 10	<i>T</i>
2 10	20
2 10	
3 15	
4 20	
5 25	
Shipper-oriented 1 5 30 10	20
2 10	
3 15	
4 20	
5 25	

Table 6 Datasets based on the varying number of each echelon



Fig. 6 Disruption costs in terms of gaps (percentages)



Fig. 7 Usage gaps for street-turn and repositioning (percentages)

disrupted utilization for 
$$ECR = \frac{(r_{\text{REST}}^* - r_{\text{RCNF}}^*)}{r_{\text{BEST}}^*} \times 100$$

For example, 0% disrupted utilization shows no difference in the values of reliable and optimal solutions or does not incur any activity in the ST or ECR strategies in both models while 100% indicates completely disrupted arcs. Both types of datasets reduced the use of ST situations, whereas higher utilization of ECR activities were found in cases in which shipper nodes were changed (consignee-oriented). In contrast, repositioning activities were almost insensitive to changes in node sizes for a shipper-oriented network, showing that 0%

utilization was achieved in Datasets 1, 3, 4, and 5. This result implies that a consignee-oriented network utilizes more ST strategies while less ECR strategies are implemented in a shipperoriented network under disruption. Therefore, it gives a tip to shipping company managers that container network flows could be smoothed by providing more effective disruption management on a consignee-oriented network in terms of the ECR reliability because this network showed an unstable supply of empty containers, compared to a shipper-oriented network as illustrated in Fig. 7.

# 5.3 Effect of the demand-supply variation

In this subsection, we demonstrate how to affect expected total relevant costs by applying different scales of the demand–supply variation, denoted by  $\Delta_{DS}$ . This value is calculated in the following manner:

$$d_{DS} = E\left(D_{jt}^{p}\right) - E\left(L_{it}^{p}\right) \text{ for } E\left(D_{jt}^{p}\right) > E\left(L_{it}^{p}\right)$$

We noted that the value of  $\Delta_{DS}$  indicated an average degree of imbalance of empty containers held between each region. We tested 27 instances with varying key parameters and a different degree of average imbalance, generated from  $q, s \in \{0.1, 0.2, \dots 0.9\}$  and  $d_{DS} \in \{5, 10, 20\}$ . The greater the  $\Delta_{DS}$ , the more the imbalance intensified. The optimal cost generated from the non-disruptive model was used as a benchmark, and disruption costs were expressed in gaps (percentages). Figure 8 shows that fewer disruption costs were incurred as  $d_{DS}$  increased within the same group of q and s, and that the costs belonging to the same group substantially increased until q = s = 0.50. Thereafter, increases of the costs became



Fig. 8 Disruption costs in gaps (percentages) based on different degrees of  $d_{DS}$ 



Fig. 9 Expected repositioning failure costs based on DS variability

steady for q, s > 0.5. This bar graph illustrates that container network flow could be more vulnerable to disruption, even in lower degrees of imbalance. In other words, an increase in ECM strategies triggered by an increase in  $d_{DS}$  did not disturb container flow and helped maintain reliability over disruption.

Furthermore, a higher average degree of imbalance caused a higher risk in implementing ECM strategies. In Fig. 9, although the expected failure costs of ECR for three levels of  $d_{DS}$  reached almost zero for  $q, s \ge 0.60$ , the growth rates of higher  $d_{DS}$  showed an increasingly steep slope until q, s = 0.50. Therefore, it is implied that a larger imbalance between empty container demand and supply is accompanied by a greater risk in ECR. Our findings also highlighted that no failure costs would be incurred after q, s > 0.70, due to the absence of repositioning activities.

## 5.4 Managerial insights

To summarize results in Sect. 5, our computational experiments showed significant variation in disruption costs (percentage), expected cost terms, and reliable solutions with a different degree of risk in disruption on the basis of comparison with the benchmark model, which is assumed to be the best-case scenario without characterizing the nature of disruption in its deterministic formulation. With our sensitivity analyses, we showed that disruption costs may rise significantly if no appropriate action were to be taken by management. Because node- and arc-failures severely impede the flow of empty containers supplied by two main container supply sources from consignees (ST) and ports (reusing), one can pinpoint each region where disruption is more often reported, and can therefore frequently reposition empty containers, whenever needed, to ensure a certain level of reliability. We also observed that no remarkable difference existed between the benchmark and RCNF models in terms of expected total relevant costs and total volumes of ECM strategies used in computational experiments. This remained the case until certain levels of disruption probabilities were met and implies that managers of shipping companies should carefully implement reliable strategies by conducting in-depth investigations of disruptions that occur in regions where their interests lie.

Throughout the sensitivity analyses, the ECR strategy is far more vulnerable to the impact of disruption than is the ST strategy in terms of disruption costs. This is mainly attributable to the fewer numbers of empty containers available; that is, the ECR strategy is implemented between the fewer numbers of ports by maritime transportation, while the ST strategy is conducted between the larger numbers of consignees and shippers, as well as being supplemented by the ECR through hinterland transportation. More connectivity between consecutive echelons could prevent supply vulnerability from potential disruption. Therefore, management could promote a higher level of shipping conference in which companies' shipping service routes and container slots in vessels are freely shared, instead of the normal situation in which companies aggressively compete with one other, especially during times of higher uncertainty.

From the perspective of the storage level of empty containers at ports, failure costs significantly affect the ECR and ST costs, based on the degree of risk in disruption. After exceeding a certain threshold point of disruption probabilities, all of the corresponding arcs are almost completely blocked so that some import-oriented ports may suffer from extremely high storage levels due to the disrupted ECR strategy (see Fig. 5). On the other hand, disruption in the ST strategy had less impact on storage levels when ports retained sufficient empty containers (see Fig. 4). Therefore, management could properly distribute their empty containers from the region where the surplus of empty containers is often held to another region that is most likely suffering from disruption. This proactive disruption management solution is practical, because shipping companies maintain rich historical disruption data on their respective regions.

# 6 Conclusions

This paper developed a reliability model for the RCNF problem to design reliable container shipping networks by using various ECM strategies, such as ECR, reusing, returning, storage, and implicitly leasing empty containers. This paper also explored the impact of disruption on shipping container network design by comparing models with the benchmark model, which was based on a deterministic formulation that did not take into account disruption occurrences. Sensitivity analyses on disruption costs were offered in Sect. 5, and expected cost terms, including expected failure costs for ST and ECR situations, were studied. This paper also investigated reliable solutions for the RCNF model with respect to varying key parameters, such as disruption probabilities and the size of echelons.

We also showed uncertain situations in which the disruption probability of inducing nodeand arc-failures was escalated to provide some managerial insights and implications. That is, we showed that reliable solutions did not remarkably differ from those of the benchmark model until a certain degree of risk from disruption was reached; and we showed that expected total relevant costs stayed constant after a certain level, as well (see Figs. 3, 4, and 7). Despite the fact that the shipping container supply chain is vulnerable to the disruption that causes damage to supply arcs, our model offers proactive measures to cope with disruptions that are triggered by natural disasters, labor strikes, failures in facilities, administrative interruptions, and other unforeseen circumstances. Our model does this by designing a more reliable shipping container network with ECM strategies to counteract the impact of disruption and achieve robustness in supply capability.

Amid all these findings, however, we admit the following limitations of this paper: (i) we need to relax the hard assumption to consider another disruption in port-handling capacities, such as outages of quay-cranes, as well as arc flow capacity between each echelon, instead of complete closure; (ii) because the RCNF model is another form of a stochastic program, known for having a high computational complexity, it would be better to develop heuristic algorithms to cope with large-scale instances, which are frequently encountered in practice; (iii) a port storage capacity should also be taken into account, because it is closely related to the profit generation of a shipping company. The more empty containers that occupy storage areas at a port, the less opportunity there is to handle laden containers. This contradicts our claim that more repositioned containers are helpful in combatting frequent disruptions. Hence, establishing a trade-off between the occupation of empty and laden containers is another important aspect for the DM. On the other hand, it would be better off to design reliable container networks based on a hub-and-spoke system in which trans-continental shipments take place in some important hub ports. Such a system is widely known to the ECR problem and could benefit from an increase in reliability. Moreover, various types of shipping containers bring advantages in cost and space savings in the overall shipping system, such as foldable and combinable containers. These containers are very effective in reducing the volume of empty containers required and can contribute to better forestallments of disruptions.

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# Appendix

See Tables 7, 8,9 and 10.

s	q	Z <sub>RCNF</sub> (\$)	E(street-turn) (\$)	E(failure) (\$)	E(repositioning) (\$)	E(failure) (\$)
0.45	0.20	38,406,262	2,599,498	8,738,657	1,983,176	13,683,657
	0.25	40,423,559	2,401,115	10,754,005	1,983,176	13,683,657
	0.30	42,124,361	1,477,946	8,374,229	1,968,732	13,621,066
	0.35	42,885,988	224,691	1,589,681	1,955,579	13,560,562
	0.40	42,921,303	-	-	1,955,579	13,560,562
0.5	0.20	41,487,583	2,600,330	8,738,657	1,524,946	12,894,180
	0.25	43,504,203	2,395,711	10,724,320	1,524,736	12,892,980
	0.30	45,189,392	1,466,380	8,296,707	1,511,064	12,780,180
	0.35	45,941,644	222,507	1,573,340	1,502,371	12,704,370
	0.40	45,976,955	-	-	1,502,003	12,700,210
0.55	0.20	43,039,805	2,602,475	8,729,288	65,000	628,821
	0.25	45,031,254	2,318,684	10,355,327	64,578	626,010
	0.30	46,649,858	1,401,899	7,914,277	64,425	626,010
	0.35	47,372,257	218,420	1,543,668	64,134	626,010
	0.40	47,407,121	_	_	64,188	626,010
0.60	0.20	43,195,255	2,602,589	8,729,288	64,690	768,285
	0.25	45,186,704	2,318,847	10,356,033	64,578	768,285
	0.30	46,805,308	1,401,675	7,912,981	64,425	768,285
	0.35	47,527,707	218,420	1,543,668	64,134	768,285
	0.40	47,562,571	_	_	64,188	768,285

Table 7 Key cost components for Figs. 4 and 5

	1	e					
s	q	$y_{ijt}^{p}^{*}$ (unit)	$q_{pjt}^{*}$ (unit)	$\delta_{jt}^{p *}$ (unit)	z <sub>ipt</sub> * (unit)	$IE_t^{p*}$ (unit)	$r_{pp't}^{*}$ (unit)
0.45	0.20	30,113	14,025	1022	15,068	3,932	12,782
	0.25	29,654	14,484	1022	15,527	3,932	12,782
	0.30	19,295	24,813	1052	25,886	4,082	12,722
	0.35	3191	40,888	1081	41,990	4,227	12,664
	0.40	-	44,079	1081	45,181	4,227	12,664
0.5	0.20	30,113	12,556	2491	15,068	17,879	9844
	0.25	29,574	13,095	2491	15,607	17,859	9844
	0.30	19,118	23,507	2535	26,063	18,558	9756
	0.35	3159	39,438	2563	42,022	18,956	9700
	0.40	-	42,595	2565	45,181	19,003	9696
0.55	0.20	30,081	7864	7215	15,100	113,313	396
	0.25	28,571	9373	7216	16,610	113,384	394
	0.30	18,246	19,698	7216	26,935	113,328	394
	0.35	3100	34,844	7216	42,081	113,384	394
	0.40	-	37,944	7216	45,181	113,389	394
0.60	0.20	30,081	7863	7216	15,100	113,338	394
	0.25	28,573	9371	7216	16,608	113,384	394
	0.30	18,243	19,701	7216	26,938	113,328	394
	0.35	3100	34,844	7216	42,081	113,384	394
	0.40	-	37,944	7216	45,181	113,389	394

Table 8 Optimal solutions for Figs. 4 and 5

	Datasets	$Z_{RCNF}(\$)$	$Z_{Best}(\$)$	$y_{ijt}^{p}$ *RCNF	$r_{pp't}^{*}$ Best (Unit)	$r_{pp't}^{*}$ RCNF (Unit)	$y_{ijt}^{p}$ Best
				(Unit)			(Unit)
Consignee-oriented	1	24,155,326	4,556,387	1,597	I	7,419	I
	2	39,558,948	76,25,011	4,638	I	14,696	I
	3	47,679,464	9,458,067	7,946	17	21,643	162
	4	51,069,377	11,470,744	10,207	2,291	24,794	3,672
	5	47,564,453	12,372,246	14,237	3,745	27,609	7,620
Shipper-oriented	1	21,828,964	18,928,117	4,337	I	7,448	I
	2	21,621,772	15,898,317	7,088	I	14,889	429
	c,	21,901,095	13,297,898	10,808	120	21,809	120
	4	25,563,229	12,460,706	12,800	2,068	24,806	2,068
	5	30,682,314	11,857,082	15,697	4,708	27,668	4,768

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$Z_R$	S = 5			$\Delta_{DS} = 10$			$\Delta_{DS} = 20$		
	CNF(\$)	Z <sub>Best</sub> (\$)	$Z^F_{re}$ (\$)	$Z_{RCNF}(\$)$	$Z_{Best}$ (\$)	$Z^F_{re}$ (\$)	$Z_{RCNF}(\$)$	$Z_{Best}$ (\$)	$Z^F_{re}$ (\$)
0.10 36,	463,071		3,683,027	49,824,298		5,652,550	79,932,967		9,366,679
0.20 45,	618,391.9		8,286,810	61,752,644		12,718,237	96,974,434		21,105,528
0.30 55,	996,724		14,205,960	75,661,307		21,750,107	117,527,261		36,197,169
0.40 65,	557,284		22,098,160	89,814,853		33,769,500	140,566,858		56,245,680
0.50 77,	251,998	22,276,326	24,822,190	107,750,363	31,939,184	40,608,390	170,015,668	51,889,952	62,210,700
0.60 79,	716,815		937,605	112,642,352		1,527,420	177,278,255		2,432,850
0.70 80,	229,861		852,227	113,614,201		1,512,653	178,717,194		2,938,366
0.80 80,	250,365		I	113,678,024		I	178,827,438		Ι
0.90 80,	250,365		I	113,678,024		I	178,827,438		Ι

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