Journal of Quality Engineering and Production Optimization

Vol. 5, No. 2, Summer & Autumn 2020

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/JQEPO.2020.2874.1056

Reliable Supply Chain Network Design Considering Resilience Strategies Under Risk of Disruption

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Abstract *– This paper presents a scenario-based supply chain network design (SCND) model in the case of disruption occurrence with a single product type. The proposed supply chain (SC) comprises three echelons, including manufacturers, distribution centers (DCs), and customers. Two kinds of DCs, namely reliable and unreliable DCs, are considered in the presented model. Disruption affects unreliable DCs and causes the loss of a portion of their capacity. Thus, an unreliable DC capacity in each period is assumed to be a positive variable specified based on its capacity in the previous period. There are different investment levels for establishing each DC, which affects the amount of capacity loss due to disruption. Two resilience strategies, DC capacity fortification and inventory keeping are considered to reduce the effects of disruption on SC, and the results under each strategy are investigated. The outcomes are investigated by presenting numerical examples, and the advantages of the proactive manner versus reactive manner are shown. Finally, sensitivity analysis is done on disruption related parameters to show how parameters influence the model outputs.*

Keywords*– distribution centers, resilience, risk of disruption, supply chain management.*

I. INTRODUCTION

In supply chain network design (SCND) problems, different decisions at different stages are made. The facilities' location and capacity are categorized as long-term decisions, and inventory level and material flow are related to operational level decisions. It should be noted that operational decisions are affected by long term decisions. Thus, these decisions should be addressed simultaneously (Farrokhi-Asl et al., 2020). Since SCND includes decisions at different stages of the design, uncertainty is its common and undeniable part. Therefore, designing a resistant SC against uncertainty and risks seems essential. Tang (2006) explained risks are classified into two categories, operational risks and disruption risks. Operational risk refers to the risk in demand and supply parameters, while disruption risk is caused by human-made or natural disasters such as floods, earthquakes.

Furthermore, supply chain resilience is a growing concern in designing supply chain networks, which ensues from globalization, leading to different disturbances. Such disruptions in supply chain networks need to be managed efficiently, compelling the utilization of approaches that can support resilient supply chain decisions. According to recent studies conducted in this field of study (Ribeiro and Barbosa-Povoa, 2018; Hosseini et al., 2019; Rabbani et al., 2020), resilience management is the most critical issue for supply chain management and feeds simply into the success of supply chains. It can be asserted that resilience is at the heart of current supply chain management and investing in

Manuscript Received:2- Sep -2020 & Revised: 4- Oct -2020 & Accepted: 30- Dec -2020
ISSN: 2423-3781

resilience leads to the agile supply chains that quickly act to and rebound from disruptions.

This paper considers disruption risk and its effect on designing the SC network. There are two kinds of strategies to deal with disruption risk, proactive and reactive strategies. A proactive strategy is conducted before disruption happening, while a reactive strategy is in response to disruptions. Moreover, we address the problem of designing a supply chain network. This paper's main decisions are facility location, the flow of products, and inventory level. Facilities are prone to disruption at any time, and the main effect of disruption is the loss of the portion of their capacity. A scenario-based model is used to model a disruption. Different scenarios are defined, and the occurrence probability of each scenario is known. Facilities can be established with different levels of investment. The higher the investment in facility establishment, the lower the capacity loss under disruption occurrence. As a result, there is a tradeoff between opening facilities with more investment levels to lower capacity loss during the planning horizon and opening facilities with fewer investment levels to control SC's total cost. Two proactive strategies are facility fortification and inventory keeping considered to increase SC resilience at the proactive planning stage. Each facility can be fortified to gain a portion or all of its lost capacity. Additionally, finished products can be stored in DCs as an inventory. The paper's objective is to design SC network which has a minimum total cost by determining facility locations from potential candidate locations, production planning, and distribution planning.

The remainder of the paper is organized as follows. In section 2 we present a brief literature review related to our work. In section 3 the mathematical formulation of SCND under disruption occurrence is presented as a mixed-integer-nonlinear model. Section 4 is devoted to numerical examples and results related to different cases. In section 5, a comparative analysis is presented. Finally, sensitivity analysis on several parameters is done.

II. LITERATURE REVIEW

As an outcome of recent year's evolution, the role of SC in global business overgrows. Furthermore, SCs are extended beyond the boundary of a country to a global issue. These changes make SCs susceptible to undesirable events more than before. The undesirable event, known as disruptive event or disturbance, is a foreseeable or unforeseeable event, which directly affects the usual operation and stability of an organization or an SC" (Barroso et al. 2011). Many researchers have concentrated on SC design to decrease such events' adverse outcomes in response to the challenges mentioned above. In this section, we present the literature review related to our work. We divide the literature review into two sections. At first, the SC disruption literature is described, and then several SC resilience strategies are explained.

A. SCND under disruption and uncertainty

Since the importance of service level increases, considering disruption and uncertainty can help firms satisfy customers' demands in a higher level of service and better. In the last decade, SC disruption has been received more attention, and many researchers have conducted experiments in this field.

The Supply chain may encounter two classes of uncertainties, including operational uncertainty and unexpected disruptions. The first class of uncertainties, which may occur frequently, have considerable impacts on the SC performance. The uncertainties in customers' demand, raw material prices, and other issues in supply and procurement processes are stratified as the first class. A variety of research in designing SC, considering operational uncertainties only on the demand-side, has been performed in the literature (Cardona-Valdés et al., 2011; Qiu & Wang, 2016). Several research pieces have taken into account the uncertainty on the supply-side (Bode & Wagner, 2015; Giri & Bardhan, 2015; Rabbani et al., 2020).

In recent years many researchers have considered the disruption in designing SC networks. Drezner (1987) proposed two facility location models that consider the impact of disruption on facilities. In the first model (P-median model), the impact of disruption is investigated on facility location and the path between facilities. This model aims to minimize the traveling distance. In the second model (p-q center problem), the impact of disruption is appeared on facilities to be located. This model aims to minimize the distance between the closest facilities to their customers.

Snyder & Daskin (2005) investigated a facility location problem by considering reliability and fixed costs for establishing facilities in the P-median problem. In another work, a mixed-integer mathematical model is formulated. This model aims to minimize the effects of disruption and achieve a stable condition after disruption, which is defined as resilience. Another model for SCND is proposed by Jabbarzadeh et al. (2012). In this model impact of disruption is appeared on facilities that have to be located. This paper's significant decisions are facility location, allocation decisions related to allocating customers to located facilities, and the flow of products between selected nodes. The model is formulated as a non-linear mixed-integer programming model. Supplier selection is another decision that is affected by disruption occurrence. In research conducted by Torabi et al. (2015), the operational and disruption risks are considered in two-echelon SC with supply facilities and demand nodes. This study decides about selecting suppliers and allocating orders to each supplier in the case of occurring disruption. Sadghiani et al. (2015) presented a retail network design problem considering risks. Two kinds of risks are considered operational and disruption risks. A possibilistic scenario-based robust model is presented, and the superiority of the proposed model over the case where the disruption and operational risks are not considered is investigated using numerical analysis. Simchi-Levi et al. (2013) incorporated inventory keeping and multiple sourcing as disruption mitigation strategies into a model that also considered demand uncertainty. Azad et al. (2014) presented the SCND model in which random disruption is considered. Disruption affects transportation modes and unreliable DCs where they may lose a fraction of their capacity because of disruption. Constructing reliable DCs which are not affected by disruption and using safe transportation modes are the strategies used in this paper to reduce the effects of disruption.

Hasani & Khosrojerdi (2015) presented an SCND model under correlated disruptions and demand, and procurement cost uncertainty using robust optimization along with scenario-based modeling. They considered six proactive and reactive resilience strategies. One of the strategies used by them is DC fortification, which is limited to be done at most one time during the planning horizon. Recently, Moradi et al. (2019) introduced an integrated framework regarding principal component analysis (PCA). They presented a multi-objective possibilistic mixed-integer programming (MOPMIP) model to find an optimum design of a supply chain network under uncertain conditions. The PCA approach is applied for the ranking of suppliers. The proposed mathematical model is also utilized to construct the agile supply chain network under uncertainty.

B. SCND considering resilience (resilient SC design)

There are different definitions of SC resilience presented in various research: one of the definitions presented by (Ponomarov & Holcomb, 2009) is as follows: "SC resilience is the adaptive capability of the SC to prepare for unexpected events, respond to disruptions and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". Another definition, which is a comprehensive one, presented by Ponis & Koronis (2012), and it is as follows: "SC resilience is the ability to proactively plan and design the SC network for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post robust state of operations, if possible a more favorable one than that before the event, thus gaining a competitive advantage". Moreover, Gholami et al. (2019) proposed a four-echelon supply chain network including suppliers, plants, distribution centers, and demand points. In this paper, the procurement of raw materials and products is affected by random disruptions based on environmental conditions, natural disasters, and ownership changes. This paper is the first research considering the uncertainty and reliability of the problem's parameters with multiple products.

C. SC resilience strategies

An enterprise or an SC can use two kinds of strategies when it faces disruption, proactive and reactive strategies. The proactive strategies help SCs avoid disruptive events rather than respond to disruptive events, while reactive strategies are mostly applied to an event. Much more of the SC resilience literature is dedicated to SC resilience strategies.

Proactive strategies: There are several studies on different proactive strategies. Increasing visibility, which enables the SC to see all of its elements, is one of several researchers' proactive strategies (Carvalho et al., 2012; Sáenz & Revilla, 2014; Silva et al., 2017). The collaboration with other cooperation in other parts of the SC, such as information sharing, is another proactive strategy considered by Carvalho et al. (2012), Pettit et al. (2013), and Scholten et al. (2014). The inventory management in order to mitigate and reduce inventory risks (Boone et al., 2013; Ghomi & Asgarian, 2019), appropriate supplier selection (Rabbani et al., 2020), information technology as a means to increase visibility (Erol et al., 2010) are other proactive strategies considered in the literature.

Reactive strategies: There are studies on investigating reactive strategies. The SC Agility, which is defined as "the ability of an SC to respond to change by adapting its initial stable configuration rapidly" (Wieland & Wallenburg, 2013), is considered by many researchers (Ponis & Koronis, 2012; Scholten et al., 2014). Flexibility, which is defined as "the ability of an enterprise to adapt to the changing requirements of its environment and stakeholders with minimum time and effort" (Erol et al., 2010), is another reactive strategy considered by Mensah & Merkuryev (2014). The redundancy is another reactive strategy which "involves the strategic and selective use of spare capacity and inventory that can be invoked during a crisis to cope, e.g., with supply shortages or demand surges" (Christopher & Peck, 2004) and is considered by several researchers (Diabat et al., 2012; Xu et al., 2014; Elluru et al., 2019). Table I makes a brief comparison between the current paper and some other papers in the literature.

Table I. Comparison between the proposed approach and related papers in the literature

Paper	***Resilience strategy***		***Number of echelons in network***	***Facilities***		***Capacity reduction in disruptions***		Methodology
	Proactive	***Reactive***		***Reliable***	***Unreliable***	***Previous period***	***Disruption parameters***	
Qiu and Wang 2016		✓	3	✓	✓		✓	Robust optimization
Rabbani et al. 2020		✓	5		✓		✓	Robust optimization
Hasani & Khosrojerdi (2016)	✓	✓	3		✓		✓	Robust optimization with scenario-based modeling
Torabi et al. (2015)		✓	2	✓	✓		✓	Differential evolution Algorithm
Silva et al., 2017	✓		3	✓	✓		✓	Artificial neural network
Diabat et al., 2012	✓		5	✓	✓		✓	Risk analysis
This paper	✓	✓	3	✓	✓	✓	✓	CPLEX solver

To sum up, the contribution of this paper are summarized as follows:

- Considering both reliable and unreliable facilities in the network
- Considering simultaneous reactive and proactive resilience strategies
- Possibility of improvement DCs in the planning horizon
- Assuming a facility capacity reduction in disruptions as the function of previous periods and disruption parameters
- Investigating the impact of different parameters on the network performance

III. PROBLEM DESCRIPTION

In this paper, we design a three echelon SC network under the risk of disruption. This network comprises manufacturers, two sets of potential locations for establishing DCs, and a set of customers that receive a single type of product from a set of manufacturers through DCs (Figure 1). We assume the DCs as intermediate points where the products are shipped to demand points and can store products. Each DC has a limited and known storage capacity. There are two kinds of DCs, reliable DCs, which are resistant against disruption, and unreliable DCs affected by disruption occurrence.

A scenario-based model is used to model a disruption. Different scenarios are defined, and the occurrence probability of each scenario is known. A disruption of DCs affects the performance of all SC. Additionally, it is assumed that disruption only affects the established DCs. As aforementioned, there are two kinds of DCs, reliable and unreliable DCs. By considering each type's characteristics, disruption only affects unreliable DCs and causes to loss of a portion of their capacity. There are different levels of investment for the establishment of unreliable DCs. The amount of capacity an unreliable DC loses due to disruption depends on the investment level in establishing that DC. The more the level of investment, the less the capacity loss.

Two proactive resilience strategies are defined to strengthen the network against undesirable impacts of disruptions and increase the network's resilience. The first strategy is to strengthen DCs against capacity loss, which occurs due to disruption. The reinforcement of DCs needs additional investment in DCs construction. An established DC can be fortified limited time during the planning horizon. Inventory keeping is another strategy for increasing the network's resilience. Finished goods are kept as an inventory in DCs to enable the SC to satisfy customers at an acceptable level in the case of disruption.

This paper aims to present a mathematical model for designing a resilient SC network under the disruption condition. Two strategies are defined to improve the resilience of SC. The model's objective is to determine the optimal SC network structure that has a minimum total cost by making decisions about the selection of facility locations from potential candidate locations, production planning, and distribution planning in such a situation. Total SC's cost is composed of fixed and operational costs of the network, including costs related to establishment and reinforcement of DCs, a shipment of products throughout the network, and inventory holding and shortage costs.

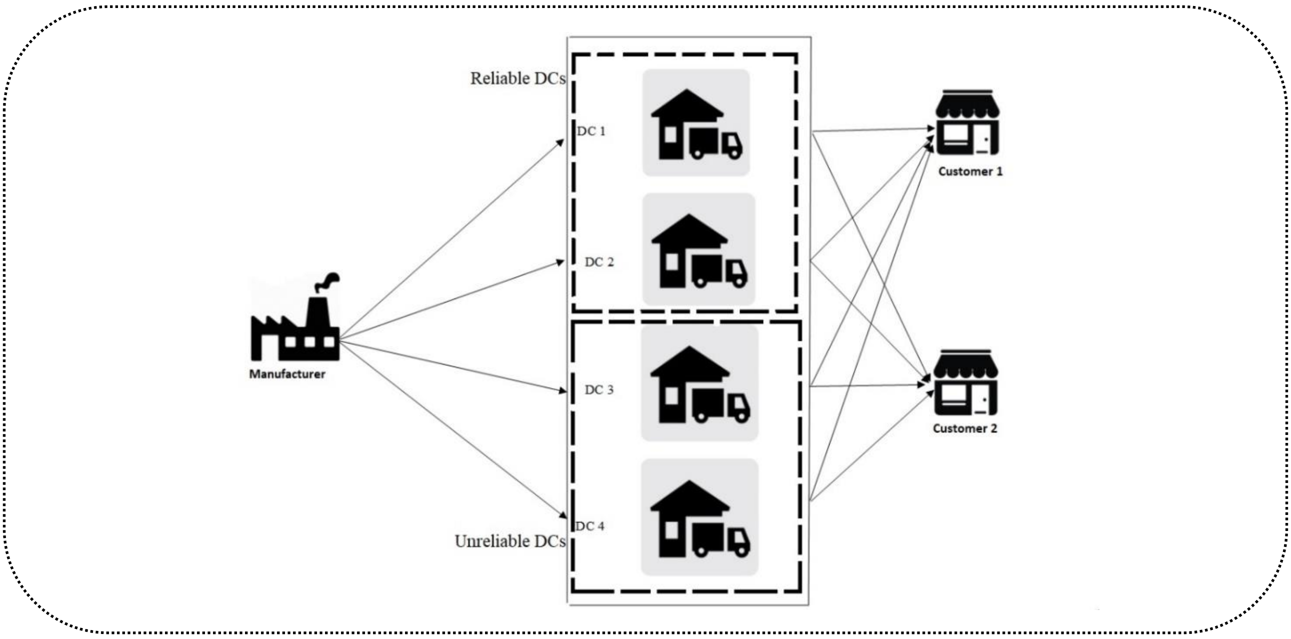

Fig. 1. The schematic of the network

A. Problem assumptions and notations

- Customers' demand is uncertain. The uncertainty in demand is incorporated into the model by considering a scenario-based model. Any unsatisfied demand is lost, and shortage appears in the form of a lost sale.
- DCs are capacitated, which means that each DC has a limited known storage capacity. The capacity of reliable DCs is known for the whole planning horizon, while unreliable DCs is known at the beginning of the planning horizon, and it is a positive variable in each period.
- An established DC can be reinforced for a limited time during the planning horizon. It is assumed that reinforcement depends on disruption occurrence. Furthermore, reinforcement in period t depends on whether the DC is reinforced from period 1 to $t-1$ or not.

The following notations are used to formulate the problem:

Indices

$m=\{1,...,M\}$	Index of manufacturers
$r=\{1,...,R\}$	Index of potential locations for reliable DCs
$u,u'=\{1,...,U\}$	Index of potential locations for unreliable DCs
$i=\{1,...,\mathrm{I}\}$	Index of potential locations for reliable and unreliable DCs
$c=\{1,...,C\}$	Index of customers
$l=\{1,...,L\}$	Index of investment levels for establishing unreliable DCs
$t=\{1,...,T\}$	Index of periods
$s=\{1,...,S\}$	Index of scenarios

Parameters

M	A huge number
p_s	The occurrence probability of scenario s
d_{cts}	The demand of customer c in period t under scenario s
FCE_{ul}	The fixed cost of establishing an unreliable DC u with investment level l
FCR_{ul}	The fixed cost of reinforcing an unreliable DC u with investment level l
FCE'_r	The fixed cost of establishing reliable DC r
e_{mi}	The unit transportation cost of a product from manufacturer m to DC i

f_{ic}	The unit transportation cost of a product from DC i to customer c
v_{ru}	The unit transshipment cost of a product from reliable Dc r to unreliable DC u
$k_{uu'}$	The unit transshipment cost of a product from unreliable Dc u to unreliable DC u'
h_i	The unit holding cost of a product for one period in DC i
g_{ct}	The unit lost sale cost of a product for customer c in period t
$Pcap_{mt}$	The production capacity of manufacturer m in period t
$Scap_r$	The capacity of reliable DC r
Cp_u	The capacity of unreliable DC u at the beginning of planning horizon
μ_{uts}	$= \begin{cases} 1 & \text{if unreliable DC } u \text{ is disrupted in time period } t \text{ under scenario } s \\ 0 & \text{otherwise} \end{cases}$
a_{ults}	The fraction of capacity of unreliable DC u with the level of investment l that is lost when the facility is disrupted in period t under scenario s
ab_{ults}	The fraction of capacity of unreliable DC u with the level of investment l which is added through reinforcement in period t under scenario s

Decision variables

XMD_{mits}	Shipment quantity of products from manufacturer m to DC i in period t under scenario s
XRU_{ruts}	Shipment quantity of products from reliable DC r to unreliable DC u in period t under scenario s
$XUU_{uu'ts}$	Shipment quantity of products from unreliable DC u to unreliable DC u' in period t under scenario s
XDC_{icts}	Shipment quantity of products from DC i to customer c in period t under scenario s
I_{its}	Inventory level at DC i in period t under scenario s, where $i \in (R \cup U \cup I)$
b_{cts}	Lost sale quantity of products for customer c in period t under scenario s
Cap_{uts}	The capacity of unreliable DC u in period t under scenario s
Z_{ics}	$= \begin{cases} 1 & \text{If customer } c \text{ is assigned to DC } i \text{ under scenarion } s \\ 0 & \text{Otherwise} \end{cases}$

$$YE_{ul} = \begin{cases} 1 & \text{If unreliable DC } u \text{ with investment level } l \text{ is located} \\ 0 & \text{Otherwise} \end{cases}$$

$$YR_{ults} = \begin{cases} 1 & \text{If unreliable DC } u \text{ with investment level } l \text{ is reinforced in period } t \text{ under scenario } s \\ 0 & \text{Otherwise} \end{cases}$$

$$N_r = \begin{cases} 1 & \text{If reliable DC } r \text{ is located} \\ 0 & \text{Otherwise} \end{cases}$$

B. Problem formulation

The multi-period single-product SCND model in the condition of disruption occurrence is formulated as a mixed-integer non-linear programming model.

$$\text{Min} \quad z = \sum_u \sum_l FCE_{ul} * YE_{ul} + \sum_r N_r * FCE'_r \tag{1-1}$$

$$+ \sum_s p_s \left[\sum_u \sum_l \sum_t \sum_s FCR_{ul} * YR_{ults} \right. \tag{1-2}$$

$$+ \sum_t \sum_i I_{its} * h_i + \sum_t \sum_c b_{cts} * g_{ct} \tag{1-3}$$

$$+ \sum_t \sum_m \sum_i XMD_{mits} * e_{mi} + \sum_t \sum_i \sum_c XDC_{icts} * f_{ic} + \sum_t \sum_r \sum_u XRU_{ruts} * v_{ru}$$
$$\left. + \sum_t \sum_u \sum_{u'} XUU_{uu'ts} * k_{uu'} \right] \tag{1-4}$$

The objective function aims to minimize total expected costs, including fixed costs of opening reliable and unreliable DCs (Eq 1-1), fortification costs of unreliable DCs (Eq 1-2), inventory holding costs in DCs, and lost sale costs for unmet demand (Eq 1-3) and shipping costs from manufacturers to DCs, from reliable to unreliable DCs, between unreliable DCs and from reliable and unreliable DCs to customers (Eq 1-4).

S.t.

$$XDC_{ucts} \le d_{cts} * Z_{ucs} \qquad \forall u, c, t, s \tag{2}$$

$$XDC_{rcts} \le d_{cts} * Z_{rcs} \qquad \forall r, c, t, s \tag{3}$$

$$\sum_m XMD_{muts} + \sum_r XRU_{ruts} + \sum_{u'} XUU_{u'uts} \le Cap_{uts} \qquad \forall u, t, s \tag{4}$$

$$Cap_{uts} = cp_u \qquad \forall u, t=0, s \tag{5}$$

$$Cap_{uts} = Cap_{u,t-1,s} * \sum_l (YE_{ul} - a_{ults} * \mu_{uts} * YE_{ul} + ab_{ults} * YR_{ults}) \qquad \forall u,t,s \tag{6}$$

$$\sum_i X_{irts} \le N_r * Scap_r \qquad \forall r,t,s \tag{7}$$

$$\sum_i XMD_{mits} \le Pcap_{mt} \qquad \forall m,t,s \tag{8}$$

$$\sum_i XDC_{icts} = d_{cts} - b_{cts} \qquad \forall c,t,s \tag{9}$$

$$\sum_c Z_{ucs} \le C * \sum_l Y_{ul} \qquad \forall u,s \tag{10}$$

$$\sum_c Z_{rcs} \le C * N_r \qquad \forall r,s \tag{11}$$

$$\sum_l Y_{ul} \le 1 \qquad \forall u \tag{12}$$

$$I_{rts} = I_{r,t-1,s} - \sum_c XDC_{rcts} + \sum_m XMD_{mrts} - \sum_u XRU_{ruts} \qquad \forall r,t,s \tag{13}$$

$$\begin{aligned} I_{uts} = I_{u,t-1,s} - \sum_c XDC_{ucts} + \sum_m XMD_{muts} + \sum_r XRU_{ruts} + \\ \sum_{u' \ne u} XUU_{u'uts} - \sum_{u' \ne u} XUU_{uu'ts} \end{aligned} \qquad \forall u,t,s \tag{14}$$

$$I_{uts} \le Cap_{uts} \qquad \forall u,t,s \tag{15}$$

$$I_{rts} \le Scap_r \qquad \forall r,t,s \tag{16}$$

$$YR_{unts} \le YE_{un} \qquad \forall u,n,t,s \tag{17}$$

$$\sum_u XRU_{ruts} \le M * N_r \qquad \forall r,t,s \tag{18}$$

$$\sum_r XRU_{ruts} \le M * \sum_l Y_{ul} \qquad \forall u,t,s \tag{19}$$

$$\sum_{u\neq u'} XUU_{u'uts} \leq M * \sum_{l} Y_{u'l} \qquad \forall u', t, s \qquad 20$$

$$\sum_{u'\neq u} XUU_{u'uts} \leq M * \sum_{l} Y_{ul} \qquad \forall u, t, s \qquad 21$$

$$I_{uts} = 0 \qquad \forall u, t = 0, s \qquad 22$$

$$I_{rts} = 0 \qquad \forall r, t = 0, s \qquad 23$$

$$\sum_{t'}^{t} YR_{unts} \leq \mu_{uts} \qquad 24$$

$$YR_{ults}, YE_{ul}, Z_{ics}, N_r = \{0,1\} \qquad \forall r, i, c, u, l, t, s \qquad 25$$

$$XMD_{mits}, XDC_{icts}, I_{its}, XUU_{u'uts}, XRU_{ruts}, b_{cts}, \mathrm{Cap}_{uts} \geq 0 \qquad \forall r, i, c, u, u', m, t, s \qquad 26$$

Constraints (2) and (3) state that there is a shipment flow from an unreliable (reliable) DC to a customer if the DC is assigned to the customer. Constraint (4) ensures that arriving products to an unreliable DC from manufacturers, reliable DCs, and other unreliable DCs are less than their capacity. The capacity of unreliable DCs at the beginning of the planning horizon is given (constraint (5)). Constraint (6) calculates the capacity of unreliable DCs in each period. An unreliable DC may lose a fraction of its capacity due to disruption occurrence. As a useful strategy, reinforcement was introduced in this paper to reduce disruption effects and to compensate for the amount of lost capacity. By reinforcing an unreliable DC, we can increase its capacity by ab_{ults}. Constraint (7) ensures that arriving products from manufacturers to a reliable DC, are less than its capacity. Constraint (8) enforces the production capacity of manufacturers. Constraint (9) states that the demand of each customer can be fully or partially satisfied. Any unsatisfied demand is considered to be lost. Constraints (10) and (11) denote that an unreliable (reliable) DC can be assigned to C customers simultaneously if it is located. Constraint (12) ensures that we can locate one unreliable DC at each potential location for unreliable DC with a specified investment level. Constraints (13) and (14) are inventory balancing constraints in reliable and unreliable DCs, respectively. The inventory level at a reliable DC at period t is constituted of the inventory at period $t-1$ plus the arriving products from manufacturers minus leaving products to unreliable DCs and customers. The inventory level at an unreliable DC at period t is constituted of the inventory at period $t-1$ plus the arriving products from manufacturers, reliable DCs, and other unreliable DCs, minus leaving products to customers and unreliable DCs. Constraints (15) enforces the capacity constraint on unreliable DCs. This constraint ensures that the inventory held in an unreliable DC in each period is less than the DC's storage capacity. Constraint (16) enforces the capacity constraint on reliable DCs. This constraint ensures that the inventory held in a reliable DC in each period is less than the DC's storage capacity. Constraint (17) denotes that an unreliable DC can be reinforced if it is established. Constraints (18) and (19) denote that there can be a transshipment flow from reliable to unreliable DCs if they are located. Constraints (20) and (21) state that there can be a transshipment flow between unreliable DCs if they are located. Constraints (22) and (23) denote that the inventory level in both reliable and unreliable DCs at the beginning of the planning horizon equal to zero. Constraint (24) limits the reinforcement of DC in a particular period to reinforce previous periods and disrupt that DC.

Constraint (25) enforces the integrality restrictions on binary variables. Constraint (26) enforces the non-negativity restrictions on decision variables. Figure 2 demonstrates a relationship between variables graphically.

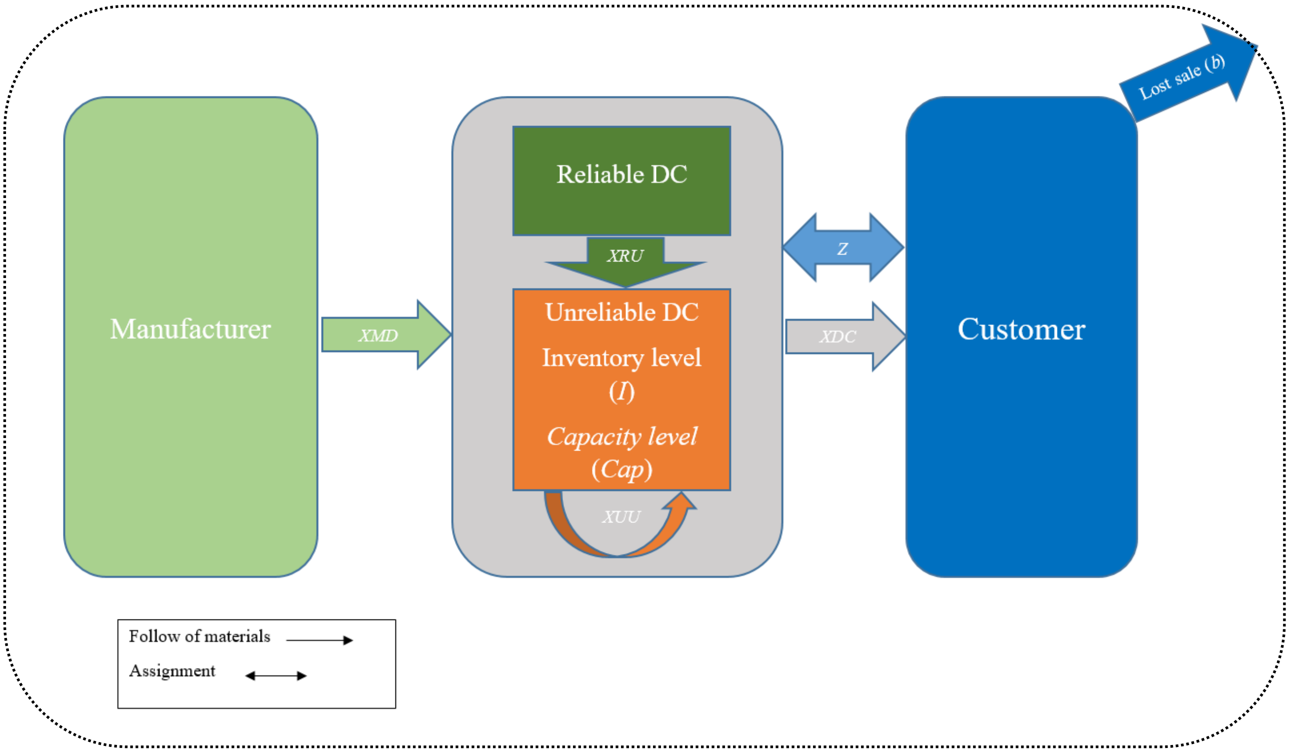

Fig. 2. Graphical demonstration of the mathematical model

As it can be concluded from the mathematical formulation, this model is a mixed-integer non-linear (non-linearity is due to the constraint (6)). Based on Sherali & Adams (2013), to transform the non-linear model to a linear one, two extra auxiliary variables, namely, $ZEXT_{ults}, ZEXTP_{ults}$ are introduced and added to the model, and constraint (6) is rewritten as Equation (27).

Constraint (6) specifies the capacity of unreliable DCs in each period. The unreliable DC may lose a fraction of its capacity because of disruption. The reinforcement strategy is applied to reduce disruption effects and to compensate for the amount of lost capacity. In this Equation, two decision variables are multiplied, so we should remove this multiplication by introducing auxiliary variables and some new constraints, namely constraints (28)-(31). $ZEXT_{ults}$ and $ZEXTP_{ults}$ are positive variables that take the value if corresponding unreliable DC is established; otherwise their value will be zero.

$$Cap_{uts} = \sum_{l} (ZEXT_{u,l,t-1,s} - a_{ults} * \mu_{uts} * ZEXT_{u,l,t-1,s} + ab_{ults} * ZEXTP_{u,l,t-1,s}) \qquad \forall u,t,s \qquad 27$$

$$ZEXT_{u,l,t-1,s} \le M * YE_{ul} \qquad \forall u,l,t,s \qquad 28$$

$$ZEXT_{u,l,t-1,s} \le Cap_{u,t-1,s} \qquad \forall u,l,t,s \qquad 29$$

$$ZEXTP_{u,l,t-1,s} \le M * YR_{u,l,t,s} \qquad \forall u,l,t,s \qquad 30$$

$$ZEXTP_{u,l,t-1,s} \le Cap_{u,t-1,s} \qquad \forall u,l,t,s \qquad 31$$

IV. COMPUTATIONAL RESULTS

A. Numerical example

A numerical example is presented to show the applicability of the proposed model. The value of parameters is shown in Table II. The proposed model has been coded within the general algebraic modeling system (GAMS) environment and solved by the CPLEX solver. All examples are tested on a personal computer with an Intel Core2 CPU and 4GB RAM.

Table II. The value of the parameter in the presented numerical example

Parameters	*value*
d_{cts}	Uniform(300,450)
$Scap_r$	Uniform(2800,2200)
$Pcap_{mt}$	Uniform(2000,2500)
a_{unts}	Uniform(0.35,0.4) for $n=1$ Uniform(0.15,0.2) for $n=2$
FCE_{ul}	Uniform(38000,40000) for $n=1$ Uniform(43000,45000) for $n=2$
FCR_{ul}	Uniform(4000,6000)
FCE'_r	Uniform(55000,65000)
h_i	15
e_{mi}	Uniform(20,30)
f_{ic}	Uniform(15,20)
v_{ru}	Uniform(8,10)
$k_{uu'}$	Uniform(8,10)
g_{ct}	Uniform(50,60)
ab_{ults}	Uniform(0.2,0.25)
p_s	0.6 for $n=1$ 0.4 for $n=2$
Cp_u	Uniform(1300,1600)

The problems are solved with the parameters indicated in Table II. The examples consist of 4 suppliers, 20 customers, three potential locations for establishing reliable depots, five potential locations for establishing unreliable depots with two investment levels for each, 12 time periods, and two scenarios. These two scenarios mainly differ on the value of the parameter μ_{uts} , which equals one if unreliable DC u is disrupted in period t under scenario s . In the first scenario, each unreliable DC is disrupted once during the planning horizon, while in the second scenario, which has a lower occurrence probability, each unreliable DC is disrupted twice during the planning horizon. The problems are considered in three cases:

1. In the first case, the problem is solved under the proactive strategy, and both the fortification strategy and inventory keeping as two resilience strategies are permissible.
2. In the second case, the problem is solved under a proactive strategy where inventory keeping is used as an only resilience strategy and DC fortification is not permissible.
3. In the third case, the problem is solved in 2 stages. First, the model is solved under the reactive strategy, which means that the disruption parameters such as μ_{uts} are excluded from the model and the DCs to be established are determined. After identifying selected DCs, these are entered as inputs to the primary model, and the model, including disruption parameters, is solved. In other words, in the first stage, DCs are established without considering disruption and its effects. Then in the second stage, DCs which are established in the first stage, can be fortified and hold inventory.

Our results show that the first case, which considers the disruptive events before selecting the optimal location for establishing DCs outperforms the other cases from the cost standpoint. It should be mentioned that since all examples in this paper have the same size, the computational time for all examples is virtually identical, and this time fluctuates between 1,263 and 1,578 seconds.

The objective function results and the main variables (established DCs and variables related to resilience strategies) for the first case are shown in Table III. The second column of Table II (u, l) shows that the unreliable, potential location u for DCs with investment level l is established. In each scenario, the results of fortification for unreliable DCs are shown in a column labeled "Fortified unreliable DCs (u, t)" where (u, t) states that if there is a fortification for unreliable DC u in period t. Two next columns show amounts of inventory held by each unreliable and reliable DC under different scenarios.

Table III. The results of the total cost, selected DCs ,and inventory level of DCs in case 1

Z ***(Total cost)***		***Selected unreliable DCs*** (u, l)	***Selected reliable DCs*** (r)
3338998.508		(2,2), (3,2), (4,2), (5,2)	(10)
Scenario	Fortified unreliable DCs (u, t)	Inventory level in unreliable DCs (u, t)	Inventory level in reliable DCs (u, t)
Scenario 1	(2,6), (4,5)	(2,8)=47.492 (2,10)=44.56, (3,6)=11.347, (5,4)=28.899	(10,5)=195.694
Scenario 2	(2,6), (3,2), (3,7), (4,5) (4,10), (5,8)	(5,5)=56.184	(10,5)=49.328

Considering Table III's results, we found out that four unreliable DCs and one reliable DC are established. As an outcome of disruption, each unreliable DC's capacity is lost, so DCs fortification is an efficient strategy for resilience used in this paper. As shown in this table, unreliable DCs are fortified to compensate for the lost capacity and enable DCs to serve customers.

In the second case, DC fortification is not permissible. The results of solving the problem under the second case are shown in Table IV. Considering DCs establishment, the difference between this case and case 1 is that the reliable DC 11 is established while unreliable DC 3 is not established. In other words, in the first case where DC fortification is allowed, just one reliable DC (DC 10) is established, and unreliable DCs (DC 2, 3, 4, and 5) are fortified several times during the planning horizon (they are fortified limited times based on constraint 24). However, in the second case where DC fortification is not allowed, reliable DCs 10 and 11 are established in addition to unreliable DCs 2, 4, and 5. The reason is that the lost sale has a penalty cost, which enforces the model to satisfy demand as much as possible. So in a tradeoff between establishing DCs to satisfy demand and paying lost sale penalty, unreliable DC 3 is substituted with reliable DC 11, which has a higher establishment cost and is resistant against disruption, and does not lose any of its capacity. Comparing the total costs of the two cases, the total costs in case 1 (3338998.508) are lower than that in case 2 (3349640.284).

Table IV. The results of the total cost selected DCs, and inventory level of DCs in case 2

Z *(Costs)*	*Selected unreliable DCs* (u, l)	*Selected reliable DCs* (r)
3349640.284	(2,2), (4,2), (5,2)	(10), (11)
Scenario	Inventory level in unreliable DCs (u, t)	Inventory level in reliable DCs (u, t)
Scenario 1	--------	(10,5)=97.181
Scenario 2	--------	(10,3)=45.213, (10,5)=46.375

The results of solving the problem under the third case are shown in Table V. As explained before; the problem is solved in two stages. Stage 1 is related to locating DCs without considering disruption effects. After locating DCs, the second stage considers the effects of disruption to located DCs, and they may lose their capacity due to disruption. In other words, the third case is a reactive manner in response to disruption. By comparing the results of the first case with the third one, it is concluded that the proactive manner outperforms the reactive manner considering the total cost.

Table V. The results of the total cost selected DCs, and inventory level of DCs in case 3

Z *(Costs)*		*Selected unreliable DCs* (u, l)	*Selected reliable DCs* (r)
3423459.601		(1,1), (3,1), (5,1)	(10), (12)
Scenario	Fortified unreliable DCs (u, t)	Inventory level in unreliable DCs (u, t)	Inventory level in reliable DCs (u, t)
Scenario 1	(1,2), (3,7)	--------	(10,5)=167.448
Scenario 2	(1,2), (1,6), (3,2), (3,7) (5,8), (5,11)	--------	(10,5)=70.683

B. Sensitivity analysis

The change of total cost concerning the change in parameter a_{unts} (which is defined as a fraction of the capacity of unreliable DC u with the level of investment l that is lost when a facility is disrupted in period t under scenario s) is shown in Figure 3. Table VI summarizes the results of this sensitivity analysis.

As can be seen, the total cost of SC increases by increasing a_{unts} . This event is because of the penalty cost related to products' lost sales, which enforces the model to establish more DCs, substitute unreliable DCs with reliable DCs, or fortify unreliable DCs more times in the planning horizon to compensate the more capacity loss. As shown in Table II, in case 1, unreliable DCs 2, 3, 4, and 5 and reliable DC 10 are established. However, by increasing a_{unts} to uniform (0.55,0.6) for n=1 and uniform (0.35,0.4) for n=2 in case 1-4, unreliable DCs 2, 4 and 5 and reliable DCs 10 and 11 are established. In other words, an unreliable DC (DC#3) is substituted by a reliable DC (DC#11).

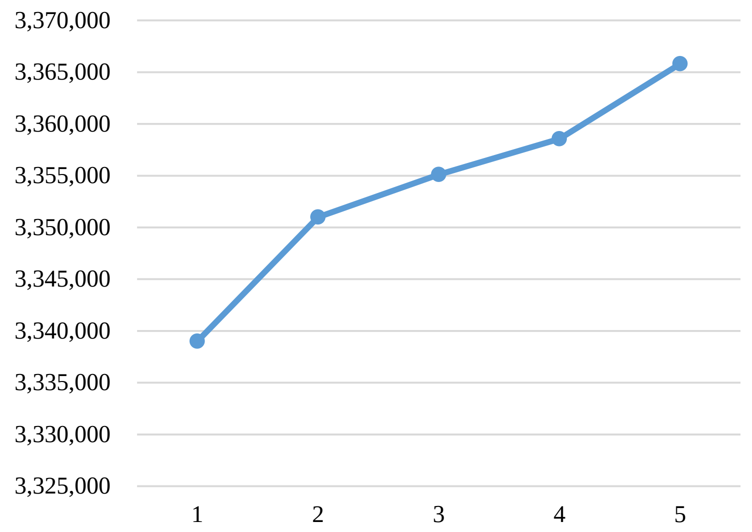

Fig. 3. The change of total cost concerning a_{unts}

Table VI. the change of total cost concerning a_{unts}

Case	a_{unts}	***Total cost***
1	For n=1 uniform(0.35,0.4) For n=2 uniform(0.15,0.2)	3,338,998.508
1-1	For n=1 uniform(0.4,0.45) For n=2 uniform(0.2,0.25)	3,350,997.478
1-2	For n=1 uniform(0.45,0.5) For n=2 uniform(0.25,0.3)	3,355,110.868
1-3	For n=1 uniform(0.5,0.55) For n=2 uniform(0.3,0.35)	3,358,561.629
1-4	For n=1 uniform(0.55,0.6) For n=2 uniform(0.35,0.4)	3,365,815.238

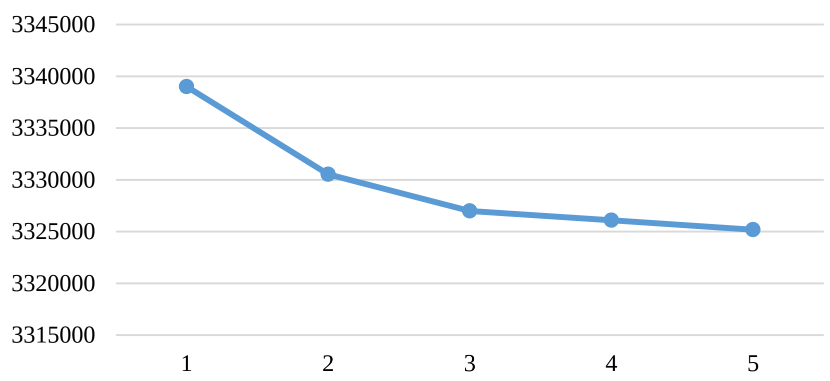

Fig. 4. The change of total cost with respect to ab_{ults}

The change of total cost for the change in parameter ab_{ults} (which is defined as the fraction of the capacity of unreliable DC u with the level of investment l added through reinforcement in period t under scenario s) is shown in Figure 4. According to this figure, the values of and total cost are shown in Table VII.

Table VII. The change of total cost concerning ab_{ults}

Case	ab_{ults}	*Total cost*
1	uniform(0.2,0.25)	3,338,998.508
1-5	uniform (0.25,0.3)	3,330,535.380
1-6	uniform(0.3,0.35)	3,326,992.857
1-7	uniform(0.35,0.4)	3,326,084.815
1-8	uniform(0.4,0.45)	3,325,184.544

As can be seen, the cost of SC decreases by increasing ab_{ults}. This event can happen because of several reasons. First, by increasing ab_{ults}, the numbers of DCs to be located may decrease. Second, the number of times fortification is done during the planning horizon may decrease. Third, the investment level for locating DCs may decrease, which means that DCs with lower opening costs and higher value a_{unts} may be established. Comparing results of case 1 with case 1-8 where ab_{ults} is increased to uniform (0.4, 0.45), it is concluded that the sum of establishment and fortification cost for case 1 (256,129.183) is higher than that for case 1-8 (249,906.736).

V. COMPARATIVE ANALYSIS

The paper is compared with the papers in the literature since it is worth noting that this paper's novelties can be evaluated in the comparative analysis section. To the best of our knowledge, no research in the literature considers the facility's capacity in disruption as the function of previous period capacity and disruption parameters. This assumption is more realistic since the disruption parameters affect the facilities' performance under disruption and previous periods' attributes are useful in this performance. Additionally, DCs possibility to expand to face disruption is a rational strategy that motivates us to apply it in our study. Few studies in the literature come up with this idea to tackle uncertainty in their models.

All in all, this study's contributions are summarized as follows: First, the capacity of an unreliable DC in each period is formulated as a recursive function of its capacity in the previous period and disruption parameters. This characteristic has not to be seen in previous works. Second, Each DC can be improved limited time during the whole planning horizon. In other words, the number of times each DC can be reinforced is not limited to at most one time during the planning horizon. In recently published studies such as Sabouhi et al. (2018), this characteristic is neglected, and in some of them, this ability is considered for DCs only in consecutive periods (Hasani & Zegordi, 2015). Third, the impact of proposed resilience strategies is investigated on SC performance by implementing a numerical approach. Also, sensitivity analysis on resilience-related parameters is conducted to investigate each parameter's impact on the solution's structure and objective function.

VI. MANAGERIAL INSIGHT

The disruption in the supply chain network may arise from natural disasters, staff strikes and economic collapse, and acts of purposeful agents such as terrorists. This paper considers disruption risk and its effect on designing the SC network. As aforementioned, two strategies can be applied to deal with disruption risk, including proactive and reactive strategies. The proactive strategy is applied before disruption happening, while the reactive strategy is in response to disruptions. According to this paper's computational results, it is highly recommended that managers use a proactive strategy. The DCs fortification is an efficient strategy for resilience that is used in this paper. As shown in this paper, unreliable DCs are fortified to compensate for the lost capacity and enable DCs to serve customers. Comparing the cost related to different strategies shows that reinforcement strategy has less cost in this problem; on the other hand, the reactive strategy in which the problem is solved in two stages has more cost. Stage 1 is related to locating DCs without considering disruption effects. After locating DCs, the second stage considers the effects of disruption to located DCs, and they may lose their capacity due to disruption. In conclusion, comparing the results of the first case with the third one, it is concluded that the proactive manner outperforms the reactive manner considering the total cost.

VII. CONCLUSION

This paper's design of a three echelon SC network under disruption is investigated, and a mathematical model is presented. Two kinds of DCs that are considered in this paper are reliable and unreliable DCs. Unreliable DCs are affected by disruption and lose a fraction of their capacity. DC fortification and inventory keeping are introduced and applied to the considered SC to reduce adverse impacts of disruption, two useful resilience strategies. Using these strategies on SC's performance is investigated through a numerical approach and by presenting three cases. Some of the obtained results are as follows: when both resilience strategies are permissible, total SC's cost is lower than when only inventory keeping is applied to the model. This is reasonable because the model can take advantage of using two strategies simultaneously. When strategies are applied proactively to confront disruption outperforms the case where the measures are reactive and respond to disruption from the total cost viewpoint. Finally, the impact of two disruption related parameters on SC's total cost and optimal values of variables are investigated.

For future study direction, we suggest that interested readers and researchers consider the uncertainty at the network's supplier side. They can use the strategies presented in this paper in order to tackle the problem. Besides, metaheuristic algorithms are efficient tools for solving optimization problems that can solve large scales. The effectiveness of these algorithms can be analyzed for solving this kind of optimization problem.

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