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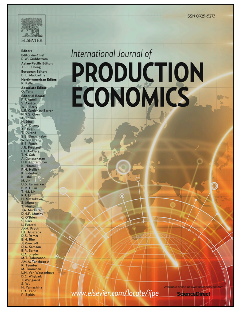

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Stochastic optimization of disruption-driven supply chain network design with a new resilience metric

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Stochastic optimization of disruption-driven supply chain network design with a new resilience metric

Abstract: The supply chain (SC) ability to return quickly and effectively to its initial condition or even a more desirable state after a disruption is critically important, and is defined as SC resilience. Nevertheless, it has not been sufficiently quantified in the related literature. This study provides a new metric to quantify the SC resilience by using the stochastic programming. Our metric measures the expected value of the SC's cost increase due to a possible disruption event during its recovery period. Based on this measure, we propose a two-stage stochastic program for the supply chain network design under disruption events that optimizes location, allocation, inventory and order-size decisions. The stochastic program is formulated using quadratic conic optimization, and the sample average approximation (SAA) method is employed to handle the large number of disruption scenarios. A comprehensive computational study is carried out to highlight the applicability of the presented metric, the computational tractability of the stochastic program, and the performance of the SAA. Several key managerial and practical insights are gained based on the computational results. This new metric captures the time and cost of the SC's recovery after disruption events contrary to most of previous studies and main impacts of these two aspects on design decisions are highlighted. Further, it is shown computationally that the increase of SC's capacity is not a suitable strategy for designing resilient SCs in some business environments.

Keywords: Resilience metrics, Supply chain network design, Stochastic programming, Conic mixed-integer program.

1- Introduction

Resilience is the ability of a system or firm to recover after a disruption event effectively and quickly, and in supply chain management, this ability is affected by SC's design decisions and resources. As emphasized by Chopra & Sodhi (2014), Simchi-Levi et al. (2014), and, Ivanov et al. (2016) from 2000 to 2015, disruption events such as economic crises, earthquakes, terrorist attacks, and strikes occurred in SCs in more frequency and severity, and hence such an ability is crucial for SCs. The Business Continuity Institute reports that one-third of 408 surveyed companies experienced at least one SC disruption in 2017 and one-fifth of the corresponding disrupted companies stated cumulative losses of at least one million euros because of disruption events (Alcantara et al., 2017). Recently, quantitative models have received significant attention to optimize design and planning decisions in SCs with consideration of disruption events, and many companies such as IBM and Ford Motor used these methods (Simchi-Levi et al., 2014; Lu et al., 2015; Hosseini et al., 2019).

A resilient SC can come back to its original state or even a more desirable condition after being disrupted (Govindan et al. 2017). To have a resilient SC, based on Tomlin (2006), a SC can take some pre-disruption actions, as mitigation strategies, to reduce its corresponding risks. On the other hand, a SC can device some actions as contingency strategies to quickly and effectively return to its initial state after a disruption's occurrence. Several studies examined these strategies in designing SC networks (see e.g., Cui et al. 2010; Qi et al. 2010; Mak and Shen 2012; Fattahi et al. 2017; Fattahi 2017; Ivanov et al. 2017). These studies concluded that more investment on SC reserves such as backup suppliers and insurance capacity increases the SC's ability in performing well after disruption events. In compared to the mitigation plans, a few papers developed contingency plans to recover a SC after disruption events. Risk management with contingency plans is investigated by Kamalahmadi and Parast (2016).

Despite a rich literature on the SC planning with consideration of disruption risks, measuring the SC resilience is still a questionable task (Pavlov et al., 2017; Hosseini and Ivanov, 2019). In other word, most of quantitative methods incorporate robustness measures into the mathematical models to maintain the SC original condition and do not consider the SC recovery after happening a disruption (Behzadi et al., 2018; Ivanov and Sokolov, 2019). In terms of optimization techniques for the SC network design, two main groups of studies can be identified for modeling the SC uncertainties induced by disruption events. In the first group (e.g., Cui et al. 2010; Qi et al. 2010; Azad et al. 2013), because of disruption events, a pre-specified failure probability for a facility/transportation link is considered, and in the second group (e.g., Mak and Shen, 2012; Klibi, and Martel, 2012; Fattahi et al., 2017; Fattahi and Govindan, 2018), the uncertainty related to the disruption impacts on a SC is modeled by a set of discrete scenarios, and stochastic programming approaches are employed. Generally, in order to measure the SC resilience, two main aspects including (1) the time of SC recovery, (2) the SC performance loss because of a disruption event should be taken into account. Further, it is a challenging task to incorporate such a resilience metric in the SC planning. The importance of shortening the recovery time after disruption events is highlighted by Sodhi and Tang (2009), and to quantify a resilience metric, a best performance is compared with the resilient solutions after a disruption occurrence in Saghafian and Van Oyen (2016) and Zobel (2011). Accordingly, this paper answers two main research questions: (1) How can a resilience metric be quantified based on the SC recovery time and its performance loss during recovery time? (2) How can a SC under disruption events be designed by consideration of a resilience metric?

To answer the above-mentioned questions, this paper introduces a new resilience metric for the SC planning as the expected increase of SC operational costs because of a disruption event during its recovery time. To incorporate the proposed resilience metric into the supply chain network design

(SCND) problem, a novel two-stage stochastic program is developed. In the first stage of the stochastic program, we optimize location, allocation, capacity, inventory, and order-size decisions of a SC system under a normal (non-disrupted) condition in which customers' demands follow a normal distribution. In the second stage, when disrupted facilities are disclosed because of a disruption event, the operational decisions should be determined over the recovery time, and allocation, inventory, and order-size decisions can be altered. Our proposed approach captures two main facets of the SC resilience consist of the recovery time and the performance loss during its recovery, and the stochastic program allows managers to quantify the impact of a disruption on the SC's operational performance.

Our optimization problem is firstly formulated as a mixed integer non-linear programming (MINLP) model and then, is reformulated as a conic quadratic mixed-integer program (CQMIP), which can be directly solved by using standard optimization software packages. On other hand, a large number of disruption scenarios make the stochastic program computationally expensive, and hence we use the SAA method to address this issue through frequently solving the optimization problem with a smaller set of scenarios.

The organization of this paper is as follows: In **Section (2)**, a literature review is represented. The stochastic program and resilience metric are proposed in **Section (3)**. In **Section (4)**, the SAA method and scenario generation approach are represented. In **Section (5)**, we present numerical experiments. **Section (6)** contains derived managerial implications. Finally, **Section (7)** contains conclusions and future research directions.

2- Literature Review

Recently, the SCND subject to disruptive events has gained much attention in both academia and practice. Various optimization models are proposed to address this problem. Lately, Snyder et al. (2016) presented a survey study related to the operations research and management science models for dealing with disruption events in SCs. Other survey studies have also focused on specific aspects of SCM under disruptions (e.g. Tang 2006; Klibi et al. 2010; Heckmann et al. 2015; Govindan et al. 2017; Dolgui et al. 2018).

A large part of studies in the corresponding area proposed an optimization model for designing a robust SC network that remains functional after a disruption event. Several studies considered a pre-determined probability for disruption of a facility and/or transportation link, and their models are also called *reliable SCND* (see e.g. Qi et al., 2010; Cui et al., 2010; Azad et al., 2013). Regarding facility disruption in some of these models, such as Cui et al. 2010, a contingency plan is proposed in which more than one facility are assigned to customers, and if a facility is disrupted, its corresponding customers should be served by other non-disrupted facilities. These studies fail to capture correlated and non-correlated multiple disruptive events. Further, the ripple effect that has been recently defined in the SC disruption literature (Dolgui et al., 2018; Pavlov et al., 2019) cannot be taken into account by this modeling approach. In particular, by the ripple effect analysis, when a disruption event happens at a facility or transportation link, we can consider further possible interruptions in the SC network. Recently, by using the SC structural dynamics control and ripple effect analysis, a few studies presented pre-disruption and recovery planning for SCs (Dolgui et al., 2018).

Scenario-based stochastic programming approaches are also popular in this area in which the uncertainty induced by natural or man-made disruptive events are modeled via discrete scenarios (see e.g., Mak and Shen, 2012; Klibi and Martel 2012; Ahmadi-Javid and Seddighi, 2013; Fattahi et al., 2017). Furthermore, weighted mean-risk objectives are employed in the stochastic programming approach to mitigate the disruption risks, and the used well-known risk measures are: the CVaR (Ahmadi-Javid and Seddighi, 2013) and the absolute deviation (Sadghiani et al., 2015). Although scenario-based approaches are relatively flexible to capture the induced SC uncertainties by disruption events, the detection of disruption scenarios and estimating their probability are challenging tasks. A few papers such as Hosseini, Morshedlou et al. (2019) and Fattahi et al. (2017) addressed these issues in using stochastic programming approaches for the SC planning under disruption events.

In the related literature, most of operations research models do not consider the recovery stage of a disrupted SC network and focus on pre-disruption SC planning that maintains the SC functionality after a disruption event. In other word, the contingency strategies are rarely addressed in compared with the mitigation ones. In the related area, as emphasized by Tomlin (2009), demand switching and contingent sourcing are the main contingency strategies. In the demand switching strategy, the SC offers incentives for a customer to buy another product if her preferred product is not available. In the contingent sourcing strategy, the SC uses a back-up supplier after a failure at its normal one. Although, the contingent sourcing is applied in Fattahi et al. (2017) and Cui et al. (2010), we could not find any paper that uses demand switching strategy for the SCND under disruption risks.

2-1- Resilience metrics

Based on Melnyk et al. (2014), currently, the resilience is the heart of SCM thinking. However, we could not find any unique definition for the resilience in the literature that presents a clear understanding of resilient SCs so that the robustness and resilience are the same in a part of the literature. In accordance with our definition, a few studies presented quantitative resilience metrics.

The ratio between actual and promised lead time, called lead time ratio, is considered as a resilience metric in Carvalho et al. (2012). To improve the SC resilience metric, they used a simulation approach that allows the observation of SC behavior under various SC design strategies. Francis and Bekera (2014) and Losada et al. (2012) quantified the SC resilience based on the required time for the SC recovery after a disruption occurrence. In Hishamuddin et al. (2013), for a lot sizing problem in a two-echelon serial SC under transportation disruption, the SC cost during its recovery time after a disruption occurrence is considered as the resilience metric. Zobel (2011) defined a resilience metric based on the reduced system's infrastructure quality in recovery time after a disruption occurrence. Saghafian and Van Oyen (2016) modeled the dynamics of disruptions as Markov chains and taken into account the disruption costs in terms of the inventory backorders over the supply shortfall. Recently, Hosseini and Ivanov (2019) presented a SC resilience metric by considering the ripple effect in both disruption and recovery stages. In this study, by a Bayesian network and the consideration of disruption propagation, the SC resilience is introduced as a function of supplier recoverability and vulnerability.

Based on the presented literature review and the existing survey studies (see Tang 2006; Klibi et al. 2010; Heckmann et al. 2015; Govindan et al. 2017; Dolgui et al. 2018) in the related areas, there exists the lack of practical resilience metrics in designing SC network. The existing metrics are not appropriate to be embedded into optimization models for the SCND. In addition, to introduce a SC resilience metric, it is essential to consider both the SC recovery time and its performance loss during its recovery. In this study, we attempt to present such a resilience metric, and to the best of our knowledge, a tractable stochastic program is proposed for the first time that optimizes the design decisions with consideration of this resilience metric. Further, a large number of disruption scenarios are handled by the SAA method in which the probability of scenarios should not be estimated.

3- Optimization Model

In this paper, a SCND problem under disruption events is formulated as a two-stage stochastic program. To consider the impact of disruption events on the SC performance, we assume that a disruption event happens for the supply chain network, and after its occurrence some of facilities will be disrupted. SC decisions should be made under normal condition without any disrupted facility as the first stage decisions. However, after a disruption occurrence, the availability of SC facilities would be realized at the second stage, and corrective SC decisions have to be determined to serve the customers.

In the SC network, multiple products should be forwarded to geographically dispersed customer zones from distribution centers (DCs). The DCs have the capacity limitation in terms of handling products. Each customer's demand follows a normal distribution, and the mean and variance related to the normal distribution of customers' demands are known. In the presented formulation, (1) location and capacity of DCs, (2) inventory decisions for DCs, and (3) allocation decisions have to be made at the time of network design before disruption events. After occurrence of a disruption event, the SC can alter the allocation and inventory decisions to fulfill the customers' demands. Further, it is possible for the SC after disruption events to not serve some customers.

Our goal is to minimize the total yearly SC cost under normal condition as well as the expected increase cost related to the DCs' disruption. The expected increase cost related to a disruption event is introduced as a new metric to measure the resiliency of a SC.

Other main assumptions are listed as follows:

- A set of candidate locations are assumed for the DCs whose locations are to be obtained in the design phase.
- For the establishment of DCs, a set of capacity levels are specified, and the SC pays a fixed location cost for activating a DC with a capacity level.
- Each DC *i* follows an inventory policy $\left(Q_{ip}, r_{ip}\right)$ for each product *p*. In this policy, by using an EOQ model, whenever the inventory level of product *p* at DC *i* falls to or bellow a reorder level r_{ip}, the DC places an order for Q_{ip} units from a supplier. In this approach, the reorder point (parameter r_{ip}) and safety stock, will be obtained to guarantee that the probability of stock-out at the DC is less than or equal to a constant value.
- Each customer should be allocated to only one open DC for receiving a product.

In this study, if a disruption event occurs, some unreliable DCs will be unavailable during the corresponding recovery time and other non-disrupted DCs have to fulfill the customers' demands. A set of discrete scenarios is used to model the impacts of disruptions on a SC network that is denoted by *K*. Set $I(k)$ contains the disrupted DCs related to scenario $k \in K$, and the corresponding recovery time $T(k)$ and recovery cost can be approximated based on the disrupted DCs in scenario *k*. As shown in **Fig. 1**, after realization of scenario $k \in K$, the operational cost of SC will be increased in compared with the normal condition of SC in which all DCs are available. The increase of the SC cost is denoted by $IC(k)$. As a new metric for the SC resilience, the expected increase cost related to a disruption event can be obtained by our formulation.

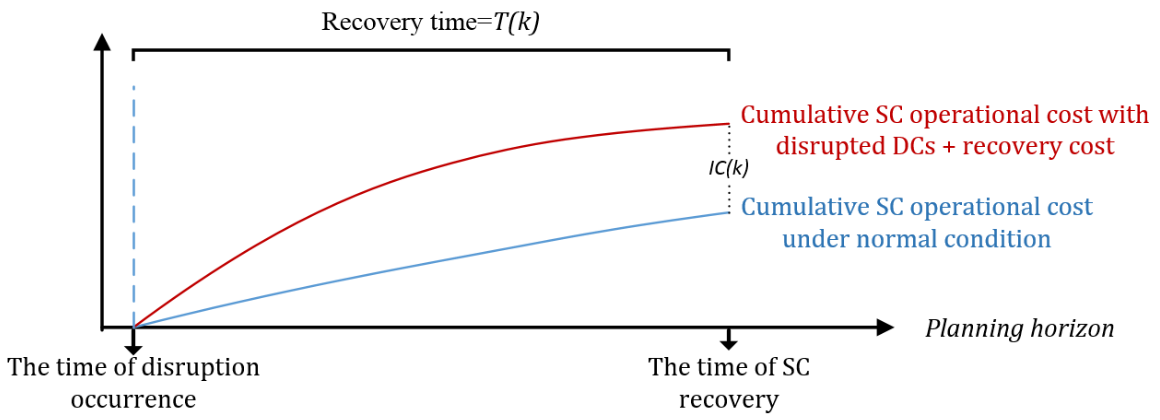


Fig. 1. The concept of defined resilience metric.

The used notations for presenting the optimization problem are reported in **Table 1**.

Table 1. The used notations in the mathematical formulation.

Sets	
J	Set of customers $(j \in J)$,
I	Set of potential locations for DCs including reliable (IR) and unreliable DCs (IU), $(i, i' \in I, IR \cup IU = I)$,
P	Set of products $(p \in P)$,
N	Set of capacity levels for the establishment of DCs $(n \in N)$,
K	Set of scenarios $(k \in K)$,
$I(k)$	Set of disrupted DCs in scenario *k*, $(I(k) \subset IU)$
Parameters	
$f_{i,n}$	The annualized fixed cost related to opening DC *i* with capacity level *n*.
$o_{i,n}$	The yearly fixed cost of operating DC *i* with capacity level *n*,
$e_{i,j,p}$	The transportation cost for forwarding one unit of product *p* from DC *i* to customer *j*,
$b_{i,n}$	The handling capacity over one year with level *n* for DC *i*,
h_{ip}	Inventory holding cost per unit of product *p* during each year at DC *i*,
d_{ip}	The fixed cost per order for product *p* placed to the supplier by DC *i*,
Lt_{ip}	Lead time of DC *i* for product *p* as a fraction of one year.
g_{ip}	The fixed cost per shipment of product *p* from supplier to DC *i*,
s_{ip}	The shipment cost for per unit of product *p* from the supplier to DC *i*,
l_p	The lost sale cost for per unit of product *p* after a disruption event,
μ_{jp}	Mean of yearly demand of customer *j* for product *p*,
σ_{jp}	Standard deviation of yearly demand of customer *j* for product *p*,
α^p	Desired percentage of customer orders for product *p* that should be satisfied,
z_{α^p}	Left α-percentile of standard normal random variable *Z*, i.e. $p\left(Z \le z_{\alpha^p}\right) = \alpha^p$,
$T(k)$	The SC recovery time after a disruption event occurrence in scenario *k*,
rc	The recovery cost related to per unit of disrupted capacity,
$\pi(k)$	The occurrence probability of scenario *k* by assuming that a disruption event will happen for the SC,
$\varphi_i(k)$	The binary indicator parameter: $\varphi_i(k) = \begin{cases} 1 & if \;\; i \notin I(k) \\ 0 & if \;\; i \in I(k) \end{cases}$
β	Weight factor associated with the resilience metric.
Decision variables	
$X_{i,n}$	1 if DC *i* with capacity level *n* is established,
$Y_{i,j,p}$	1 if customer *j* is assigned to DC *i* for product *p* under normal condition,
$Y_{i,j,p}(k)$	1 if customer *j* is assigned to DC *i* for product *p* in scenario *k*,
Q_{ip}	The order size for product *p* at DC *i* under normal condition,
$Q_{ip}(k)$	The order size for product *p* at DC *i* in scenario *k*,
OC	The yearly operational cost of SC under normal condition,
$IC(k)$	The cost increase related to the SC operation during the recovery time of the SC in scenario *k*.

3-1- Mixed integer nonlinear programming formulation:

In the proposed two-stage stochastic program, we minimize the total SC cost over one year in the first stage and the expected increase cost because of a disruption event in the second stage. Our stochastic program is formulated as an MINLP. It is worth noting that some parameters, such as $f_{i,n}$ and $b_{i,n}$, are defined based on the SC planning over one year.

Based on the used inventory policy at DCs in this study, the value of reorder point (r_{ip}) and safety stock is a function of the assignment of customers to DCs. Therefore, the parameters related to the inventory policy at each DC can be obtained in according to the optimal assignment and order size decisions after solving the optimization model (Daskin et al., 2002).

Further, it should be mentioned that a virtual un-capacitated DC, indexed by i_0, is considered, and in the case of not serving some customers after the realization of a disruption event, the SC should assign them to this virtual DC.

The objective function includes three parts: 1- the fixed cost related to the SC design, 2- the yearly operational cost of SC, 3- the expected increase cost related to DCs' disruption.

The annualized investment cost of opening DCs, given as $\sum_{i\in I}\sum_{n\in N} f_{i,n}X_{i,n}$. Therefore, parameter $f_{i,n}$ is the annualized fixed cost related to opening DCs that can be approximated based on the project life (in years) and the corresponding interest rate (Fattahi and Govindan, 2018).

The yearly operational cost of SC can be obtained by summation of the following components:

1- The fixed operating cost of DCs in one year, given as $\sum_{i\in I}\sum_{n\in N} o_{i,n}X_{i,n}$.,

2- At each DC, the variable operational cost contains the fixed cost of placing orders, the holding of working inventory cost, the safety stock cost, and the shipment cost from suppliers to DCs. Where $Q_{i,p}$ represents the order size for product *p* at DC *i*, the fixed cost of placing orders and holding cost of working inventory for product *p* are $d_{i,p}\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}}$ and $h_{i,p}\frac{Q_{i,p}}{2}$, respectively. Since the optimal value of r_{ip} is $z_{\alpha^p}\sqrt{Lt_{i,p}\sum_{j\in J}\sigma^2_{j,p}Y_{i,j,p}}$, the safety stock cost is $h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}\sum_{j\in J}\sigma^2_{j,p}Y_{i,j,p}}$. Further, the expected shipment cost from supplier to DC *i* for product *p* is $s_{i,p}\sum_{j\in J}\mu_{j,p}Y_{i,j,p} + g_{i,p}\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}}$ that includes fixed and variable shipment costs.

3- For product *p*, the shipment cost from DCs to customers, given as $\sum_{i\in I}\sum_{j\in J} e_{i,j,p}\mu_{j,p}Y_{i,j,p}$.

The two-stage stochastic program is as follows:

$$\min \sum_{i\in I}\sum_{n\in N} f_{i,n}X_{i,n} + \sum_{i\in I}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p} + \sum_{i\in I}\sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}\right)$$
$$+\sum_{i\in I}\sum_{p\in P}\left(d_{ip}+g_{ip}\right)\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}} + \sum_{i\in I}\sum_{p\in P} h_{i,p}\frac{Q_{i,p}}{2} + \sum_{i\in I}\sum_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}\sum_{j\in J}\sigma^2_{j,p}Y_{i,j,p}} + \beta\times\sum_{k\in K}\pi(k)IC(k), \tag{1}$$

$$s.t. \quad \sum_{n\in N} X_{i,n} \le 1 \qquad \forall i\in I, \tag{2}$$

$$\sum_{i\in I} Y_{i,j,p} = 1, \qquad \forall j\in J, \forall p\in P, \tag{3}$$

$$Y_{i,j,p} \le \sum_{n\in N} X_{i,n}, \qquad \forall i\in I, \forall j\in J, \forall p\in P, \tag{4}$$

$$\sum_{p\in P}\sum_{j\in J}\mu_{j,p}Y_{i,j,p} \le \sum_{n\in N} b_{i,n}X_{i,n}, \qquad \forall i\in I, \tag{5}$$

$$OC = \sum_{i\in I}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p} + \sum_{i\in I}\sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}\right)$$
$$+\sum_{i\in I}\sum_{p\in P}\left(d_{i,p}+g_{i,p}\right)\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}} + \sum_{i\in I}\sum_{p\in P} h_{i,p}\frac{Q_{i,p}}{2} + \sum_{i\in I}\sum_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}\sum_{j\in J}\sigma^2_{j,p}Y_{i,j,p}}, \tag{6}$$

$$\boldsymbol{X}, \boldsymbol{Y} \in \{0,1\}, \tag{7}$$

$$\boldsymbol{Q} \ge 0, \tag{8}$$

where *IC(k)* can be obtained as follows:

$$IC(k) = \min: \sum_{i\in I}\sum_{n\in N} rc\times\left(1-\varphi_i(k)\right)b_{i,n}X_{i,n}$$
$$+T(k)\left(\begin{array}{l} \sum_{i\in I\setminus I(k)}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p}(k) + \sum_{i\in I}\sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)\right) \\ +\sum_{i\in I}\sum_{p\in P}\left(d_{i,p}+g_{i,p}\right)\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)}{Q_{i,p}(k)} + \sum_{i\in I}\sum_{p\in P} h_{i,p}\frac{Q_{i,p}(k)}{2} \\ +\sum_{i\in I}\sum_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}\sum_{j\in J}\sigma^2_{j,p}Y_{i,j,p}(k)} + \sum_{j\in J}\sum_{p\in P} l_p\mu_{j,p}Y_{i_0,j,p}(k) - OC \end{array}\right), \tag{9}$$

$$s.t. \quad \sum_{i\in\left(I\setminus I(k)\cup\{i_0\}\right)} Y_{i,j,p}(k) = 1, \qquad \forall j\in J, \forall p\in P, \tag{10}$$

$$Y_{i,j,p}(k) \le \varphi_i(k)\sum_{n\in N} X_{i,n}, \qquad \forall i\in I, \forall j\in J, \forall p\in P, \tag{11}$$

$$\sum_{j\in J}\sum_{p\in P}\mu_{j,p}Y_{i,j,p}(k) \le \varphi_i(k)\sum_{n\in N} b_{i,n}X_{i,n}, \qquad \forall i\in I, \tag{12}$$

$$\boldsymbol{Y}(k) \in \{0,1\}, \tag{13}$$

$$\boldsymbol{Q}(k) \ge 0. \tag{14}$$

Based on constraints (2), if a DC is established, only one capacity level must be selected. Constraints (3) guarantee that customers should be allocated to only one DC for each product. Constraints (4) assure that customers can be allocated to a DC, if the DC is activated. Constraints (5) assure that each DC cannot handle the products more than its available handling capacity during each year. Relation (6) calculates the operational cost of the SC during one year under normal condition. Constraints (7) and (8) are integrality and non-negativity constraints, respectively in which the indices of decision variables are eliminated.

After a disruption event, some DCs will be disrupted (unavailable), and the operational cost of the SC will be increased. By assuming $T(k)$ as the recovery time of the SC in scenario *k*, the SC cost during the recovery time plus the corresponding cost of SC recovery is as follows:

$$\sum_{i\in I}\sum_{n\in N} rc\times\left(1-\varphi_i(k)\right)b_{i,n}X_{i,n} + T(k)\left(\begin{array}{l}\sum\limits_{i\in I\setminus I(k)}\sum\limits_{n\in N} o_{i,n}X_{i,n} + \sum\limits_{i\in I}\sum\limits_{j\in J}\sum\limits_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p}(k) + \sum\limits_{i\in I}\sum\limits_{p\in P} s_{i,p}\left(\sum\limits_{j\in J}\mu_{j,p}Y_{i,j,p}(k)\right)\\ +\sum\limits_{i\in I}\sum\limits_{p\in P}\left(d_{i,p}+g_{i,p}\right)\dfrac{\sum\limits_{j\in J}\mu_{j,p}Y_{i,j,p}(k)}{Q_{i,p}(k)} + \sum\limits_{i\in I}\sum\limits_{p\in P} h_{i,p}\dfrac{Q_{i,p}(k)}{2}\\ +\sum\limits_{i\in I}\sum\limits_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}\sum\limits_{j\in J}\sigma^2_{j,p}Y_{i,j,p}(k)} + \sum\limits_{j\in J}\sum\limits_{p\in P} l_p\mu_{j,p}Y_{i_0,j,p}(k)\end{array}\right),$$

As a consequence, the increase cost of SC in scenario *k* can be obtained by relation (9). Further, based on our previous explanations, constrains (10)-(14) are obvious that are written for scenario *k*.

3-2- An equivalent CQMIP model

The general mathematical formulation of a conic quadratic mixed-integer program is as follows:

$$\begin{array}{l}\min\limits_{x\in X} c^T x,\\ s.t.\ \ \left\|A_i x + b_i\right\|_2 \le a_{0i}^T x + b_{0i},\ \ i=1,2,..,m',\end{array}$$

where $c\in R^n$ and *x* is the *n*-vector of decision variables, $X=\left\{(y,y'): y\in Z^p, y'\in R^k, p+k=n\right\}$, and the data are $A_i\in R^{m_i\times n}, b_i\in R^{m_i}, a_{0i}\in R^n$ and $b_{0i}\in R$ for $i=1,2,..,m'$. $\|.\|$ denotes the Euclidean norm and the constraints define the second-order cone. In recent years, there have been significant developments on solving CQMIP models, and commercial optimization software such as CPLEX can solve CQMIP models efficiently. In this section, based on an approach proposed by Atamtürk et al. (2012), the equivalent CQMIP of our two-stage stochastic program is developed. Atamtürk et al. (2012) have studied several types of joint facility location and inventory management problems with stochastic retailer demand that follows a normal distribution with mean μ and variance σ^2. However, they did not consider the impact of disruption events, and their model is extended to a two-stage stochastic program under disruption events in which the proposed resilience metric is quantified and integrated.

In the presented model (1)-(14), decision variables $Q_{i,p}$ and $Q_{i,p}(k)$ have only appeared in the objective function and we can obtain their optimal values as follows:
By assuming that $(1-\beta\times\overline{T})>0$ in our problem, where $\overline{T}=\sum_{k\in K}\pi(k)T(k)$, the objective function is convex in $Q_{i,p}>0$ and to determine the optimal value of $Q_{i,p}$, the objective function's derivative with respect to $Q_{i,p}$ is equalized to zero as follows:

$$-(1-\beta\times\overline{T})(d_{i,p}+g_{i,p})\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}^2}+(1-\beta\times\overline{T})\frac{h_{i,p}}{2}=0\,.$$

As a consequence, the optimal value of $Q_{i,p}$ is:

$$Q_{i,p}^*=\sqrt{2(d_{i,p}+g_{i,p})\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{h_{i,p}}}\,.$$

Further, such as decision variable $Q_{i,p}$, the optimal value of $Q_{i,p}(k)$ can be obtained as:

$$Q_{i,p}^*(k)=\sqrt{2(d_{i,p}+g_{i,p})\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)}{h_{i,p}}}\,.$$

Therefore, by substituting the optimal values of $Q_{i,p}$ and $Q_{i,p}(k)$ in objective function (1) and equations (6) and (9), $\sum_{i\in I}\sum_{p\in P}(d_{ip}+g_{ip})\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}{Q_{i,p}}+\sum_{i\in I}\sum_{p\in P}h_{i,p}\frac{Q_{i,p}}{2}$ is written as $\sum_{i\in I}\sum_{p\in P}\sqrt{2h_{i,p}(d_{ip}+g_{ip})\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}$, and term $\sum_{i\in I}\sum_{p\in P}(d_{i,p}+g_{i,p})\frac{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)}{Q_{i,p}(k)}+\sum_{i\in I}\sum_{p\in P}h_{i,p}\frac{Q_{i,p}(k)}{2}$ is written as $\sum_{i\in I}\sum_{p\in P}\sqrt{2h_{i,p}(d_{ip}+g_{ip})\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)}$.

By using the fact that $\boldsymbol{Y}^2=\boldsymbol{Y}$, non-linear terms $\sqrt{\sum_{j\in J}\mu_{j,p}Y_{i,j,p}}$ and $\sqrt{\sum_{j\in J}\sigma_{j,p}^2Y_{i,j,p}}$ are substituted by auxiliary variables $W_{i,p}$ and $V_{i,p}$ respectively, and constraints $\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}^2\le W_{i,p}^2,\forall i\in I,\forall p\in P\right)$ and $\left(\sum_{j\in J}\sigma_{j,p}^2Y_{i,j,p}^2\le V_{i,p}^2,\forall i\in I,\forall p\in P\right)$ are embedded into the optimization problem. In addition, we reformulate the objective function of the recourse problem, equation (9), by this approach. Finally, the two-stage stochastic program as a CQMIP formulation is presented as follows:

$$\min: \sum_{i\in I}\sum_{n\in N} f_{i,n}X_{i,n} + \sum_{i\in I}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p}$$
$$+\sum_{i\in I}\sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}\right) + \sum_{i\in I}\sum_{p\in P}\sqrt{2h_{i,p}\left(d_{i,p}+g_{i,p}\right)}W_{i,p} \tag{15}$$
$$+\sum_{i\in I}\sum_{p\in P} h_{i,p} z_{\alpha^p}\sqrt{Lt_{i,p}}V_{i,p} + \beta\times\sum_{k\in K}\pi(k)IC(k)$$

$$s.t.\quad \sum_{j\in J}\sigma_{j,p}^2 Y_{i,j,p}^2 \le V_{i,p}^2 \qquad \forall i\in I, \forall p\in P, \tag{16}$$

$$\sum_{j\in J}\mu_{j,p}Y_{i,j,p}^2 \le W_{i,p}^2 \qquad \forall i\in I, \forall p\in P, \tag{17}$$

$$OC = \sum_{i\in I}\left(\begin{array}{l}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p} + \sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}\right) \\ +\sum_{p\in P}\sqrt{2h_{i,p}\left(d_{i,p}+g_{i,p}\right)}W_{i,p} + \sum_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}}V_{i,p},\end{array}\right) \tag{18}$$

$$\boldsymbol{V}, \boldsymbol{W} \ge 0, \tag{19}$$

Constraints (2)-(5), (7), and (8), (20)

where *IC(k)* can be obtained as follows:

$$IC(k) = \min \sum_{i\in I}\sum_{n\in N} rc\times\left(1-\varphi_i(k)\right)b_{i,n}X_{i,n}$$
$$+T(k)\left(\begin{array}{l}\sum_{i\in I\setminus I(k)}\sum_{n\in N} o_{i,n}X_{i,n} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} e_{i,j,p}\mu_{j,p}Y_{i,j,p}(k) \\ +\sum_{i\in I}\sum_{p\in P} s_{i,p}\left(\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)\right) + \sum_{i\in I}\sum_{p\in P}\sqrt{2h_{i,p}\left(d_{i,p}+g_{i,p}\right)}W_{i,p} \\ +\sum_{i\in I}\sum_{p\in P} h_{i,p}z_{\alpha^p}\sqrt{Lt_{i,p}}V_{i,p}(k) + \sum_{j\in J}\sum_{p\in P} l_p\mu_{j,p}Y_{i_0,j,p}(k) - OC\end{array}\right), \tag{21}$$

$$s.t.\quad \sum_{j\in J}\sigma_{j,p}^2 Y_{i,j,p}(k)^2 \le V_{i,p}(k)^2 \qquad \forall i\in I, \forall p\in P, \tag{22}$$

$$\sum_{j\in J}\mu_{j,p}Y_{i,j,p}(k)^2 \le W_{i,p}(k)^2 \qquad \forall i\in I, \forall p\in P, \tag{23}$$

$$\boldsymbol{V}(k), \boldsymbol{W}(k) \ge 0, \tag{24}$$

Constraints (10)-(14). (25)

4- Sample Average Approximation Method

In this paper, a scenario generation approach is explained that leads to identically and independently distributed (i.i.d.) subset of scenarios related to disrupted DCs. Secondly, the SAA method is used to avoid from the computational intractability of the proposed stochastic program because of a large number of scenarios.

Scenario Generation Procedure: we generate i.i.d. scenarios for the status of disrupted unreliable facilities because of natural disruption events such as earthquake and flood. Based on the geographical area of a SC network and/or historical data, the possibility of disruption events in each district of the considered geographical area can be analyzed. Firstly, we define the possible disruption events in the corresponding geographical area as set $E, e \in E$. Secondly, we obtain the possibility weights (ω_e) for the occurrence of disruptions such that $\sum_{e \in E} \omega_e = 1$.

For each disruption event $e \in E$, the set of unreliable facilities that may be disrupted under its occurrence is denoted as I_e. The disruption probability of these unreliable facilities is approximated as $pr_i(e), \forall i \in I_e$. As an illustrative example, a part of a SC network in a specific district that may be affected under disruption event e is illustrated in **Fig. 2** and facilities 1, 2, and 5 are assumed as unreliable facilities. It should be mentioned that the detection of disruption scenarios is deeply investigated by Pavlov et al. (2019) and Ivanov et al. (2016b).

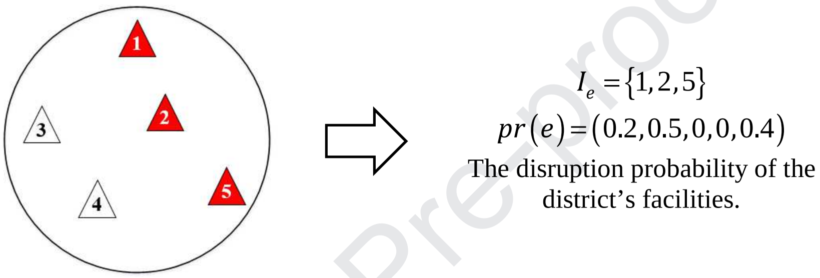


Fig. 2. SC facilities in an affected district.

Algorithm 1 presents the scenario generation procedure.

Algorithm 1. Scenario generation with *NS* samples

for all $k = 1,\ldots,NS$ **do**
  Set $I(k) = \Phi$.
  Select one disruption event *e* from set *E* by roulette wheel selection.
  for all $i \in I_e$ **do**
    Generate *U* from Uniform (0,1).
    if $U \le pr_i(e)$ **then**
      $\varphi_i(k) = 0$.
      $I(k) \leftarrow I(k) \cup \{i\}$.
    end if
  end for
  Approximate $T(k)$ based on disrupted facilities.
end for

A main challenge related to solving the stochastic program (15)–(25) is to calculate the expectation in the problem's objective. The SAA method is used to deal with this issue. In the SAA, firstly, *M* batches of *K* scenarios related to the SC disruptions are generated. Next, the stochastic problem is solved for these batches, and their objectives' average is used to estimate a lower bound for the optimal value of the problem's true objective with mean μ_L and standard deviation σ_L. Then, the obtained M feasible solutions are simulated by K' scenarios where $K' \gg K$, and the average of simulation responses for each solution is considered as an upper-bound for the problem's objective. Finally, the feasible solution with the minimum average of simulation responses will be selected for estimating the upper bound of the problem's true objective. The main steps of the SAA are illustrated in **Algorithm 2**. For more information about the SAA, one can refer to Wang (2007) and Shapiro (2001). In the SAA method, after calculating the confidence intervals for upper and lower bounds, we will obtain a $(1-\alpha)\%$ confidence interval (CI) for the optimal value of true objective as follows:

$$\left(\mu_L - t_{\alpha/2,M-1}\frac{\sigma_L}{\sqrt{M}}, \mu_U + z_{\alpha/2}\frac{\sigma_U}{\sqrt{K'}}\right). \tag{26}$$

Algorithm 2. The SAA method

1- Generate a sample of size K'.
2- **for all** $s = 1,\ldots,M$ **do**
  a- Generate a sample of size K
  b- Solve the stochastic program with the generated sample and obtain the optimal objective z_s and solution $\bar{x}_s$.
  c- Evaluate solution $\bar{x}_s$ over K' scenarios, and obtain the expected value of simulation responses as $\mu_s^{K'}$.
 end for
3- Calculate mean and variance of true objective value's lower bound:

$$\mu_L = \frac{1}{M}\sum_{s=1}^{M} z_s \text{ and } \sigma_L^2 = \frac{1}{M-1}\sum_{s=1}^{M}\left(z_s - \mu_L\right)^2.$$

4- Construct $(1-\alpha)\%$ CI for the lower bound approximation as:

$$\mu_L \pm t_{\alpha/2,M-1}\,\sigma_L / \sqrt{M}.$$

5- Obtain the best upper bound estimate and its solution as:

$$\mu_U = \min_{s\in\{1,2,\ldots,M\}} \mu_s^{K'} \text{ and } \bar{x}.$$

6- By assuming $f_k(\bar{x})$ as the problem's objective related to solution $\bar{x}$ under scenario *k* in the selected sample in *Step 5*, compute the variance of the upper bound estimate:

$$\sigma_U^2 = \frac{1}{K'-1}\sum_{k=1}^{K'}\left(f_k(\bar{x}) - \mu_U\right)^2.$$

7- Construct $(1-\alpha)\%$ CI for the upper bound estimate as:

$$\mu_U \pm z_{\alpha/2}\,\sigma_U / \sqrt{K'}.$$

5- Computational Results

Here, the results from the computational study are summarized. Our goal is to examine the tractability of the presented stochastic program and the performance of the resilience metric and, derive managerial insights regarding resilient SCs. The developed stochastic program is solved via CPLEX solver in GAMS 25.1. All implementations in this section are performed by a personal computer with Intel Core i7-640 M CPU (2.8 GHz), with 4.00 GB of RAM.

5-1- Computational efficiency of the proposed CQMIP model

Several problem instances are taken into account to examine the applicability of the CQMIP model. The model's parameters are generated based on **Table A1** in **Appendix A** by using uniform distribution according to Javid and Azad (2010) and Mak and Shen (2012). In this sub-section, four capacity levels are considered for the establishment of DCs and we randomly assumed 75% of DCs as unreliable ones. Further, each unreliable DC has 0.15 probability to be disrupted in each scenario, and parameter β is set to 1. **Table 2** illustrates characteristics of test instances, the objective function value, and CPU time from solving problem instances.

Table 2. . Computational details from solving the problem instances

Instance number	$(\lvert I\rvert, \lvert J\rvert, \lvert P\rvert, \lvert K\rvert)$	Objective function value	First stage cost	run time (S)
P1	(8, 10, 5, 15)	8.8857E+5	6.6526E+5	12
P2	(10, 12, 4, 10)	8.0121E+5	6.2327E+5	11
P3	(12, 15, 4, 15)	9.1873E+5	6.9946E+5	32
P4	(15, 18, 4, 10)	1.0722E+6	8.1057E+5	24
P5	(20, 25, 5, 15)	1.8262E+6	1.3725E+6	191
P6	(24, 28, 4, 10)	1.6349E+6	1.1972E+6	174
P7	(25, 30, 5, 10)	2.1354E+6	1.5786E+6	312
P8	(30, 40, 5, 10)	2.7238E+6	2.0308E+6	546
P9	(35, 45, 4, 10)	2.4191E+6	1.8141E+6	808
P10	(40, 50, 4, 10)	2.6621E+6	1.9785E+6	1080
P11	(45, 60, 4, 10)	3.1156E+6	2.2392E+6	1988
P12	(50, 70, 4, 10)	3.4781E+6	2.5716E+6	2932
P13	(60, 75, 4, 10)	3.5890E+6	2.6592E+6	5356
P14	(70, 90, 4, 10)	4.3510E+6	3.1547E+6	9444
P15	(100, 120, 4, 8)	6.0918E+6	4.4612E+6	14233

As shown by **Table 2**, the CQMIP model is solvable for a range of problem instances by CPLEX solver. It should be noted that in **Table 2**, the computational results are reported for some problem instances those are solvable in less than 4 hours. Further, it is illustrated that the run times are sensitive to the number of scenarios, meaningfully and hence the importance of the SAA method is highlighted.

The first stage cost that is reported in **Table 2** is the total yearly cost of the SC distribution network consisting of the fixed cost of the establishment of DCs and SC operational cost. As reported in **Table 2**, for our generated problem instances, this cost is only about 75% of the objective function, averagely, and we can conclude the value of the resilience metric in comparison with the total yearly SC cost is significant.

5-2- Application of the proposed stochastic model

One problem instance is generated in this sub-section based on the geographical area of Iran. In this problem instance 40 potential locations for DCs ($\lvert I\rvert = 40$) and 31 customers ($\lvert J\rvert = 31$) based on Iran's provinces are considered. The other characteristics of the problem instance are:

$|P|=4, |IU|=32$, and $|N|=4$. In this case example, the transportation costs are obtained from Iran's Road Maintenance and Transportation Organization, and other parameters are based on **Table A1**. The SC network, including the potential location of DCs and customers, is illustrated in **Fig. 3.**

The natural disruptions, including flood and earthquake, are considered in this case example, and **Fig 4 (a)** and **(b)** show the approximate zoning map of Iran related to the earthquake and flood hazard, respectively. Based on these figures, opinions of experts in Iran's National Disaster Management Organization, and DCs' potential locations, 40 main disruption events are assumed. In *Algorithm 1* for the scenario generation, the disruption probability of DCs in the very high, high, and moderate levels are assumed to be 0.4, 0.2, and 0.1, respectively. It should be mentioned an area that may be affected after each disruption event is also derived. We use this case example to discuss about the obtained optimal solution and resilience metric from solving the stochastic program.

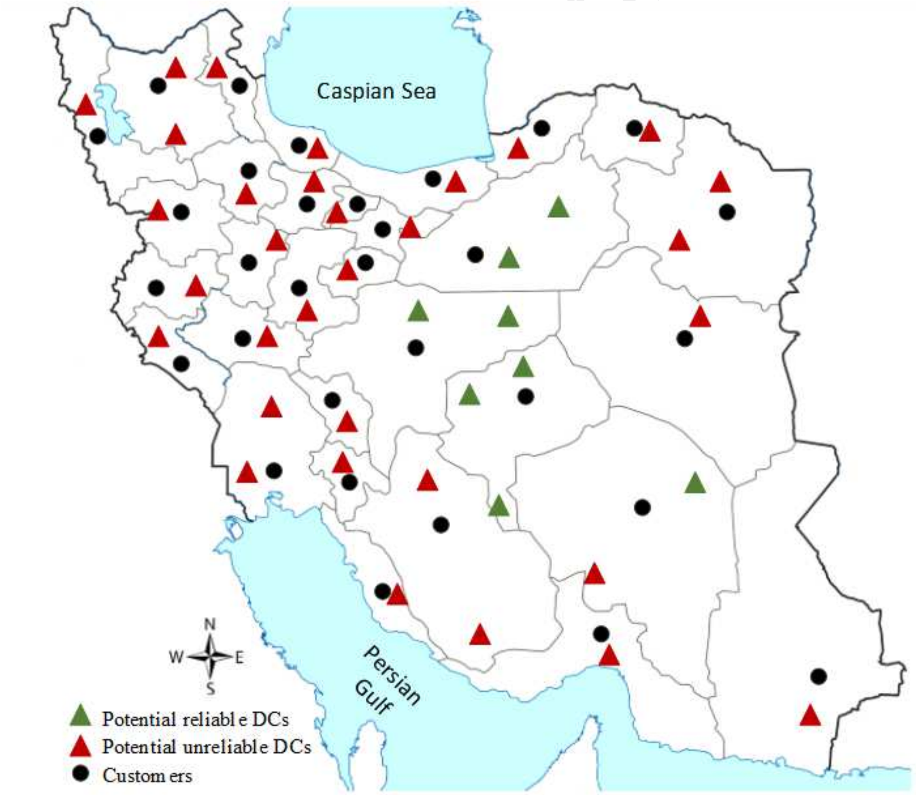


Fig. 3. The network of the case example.

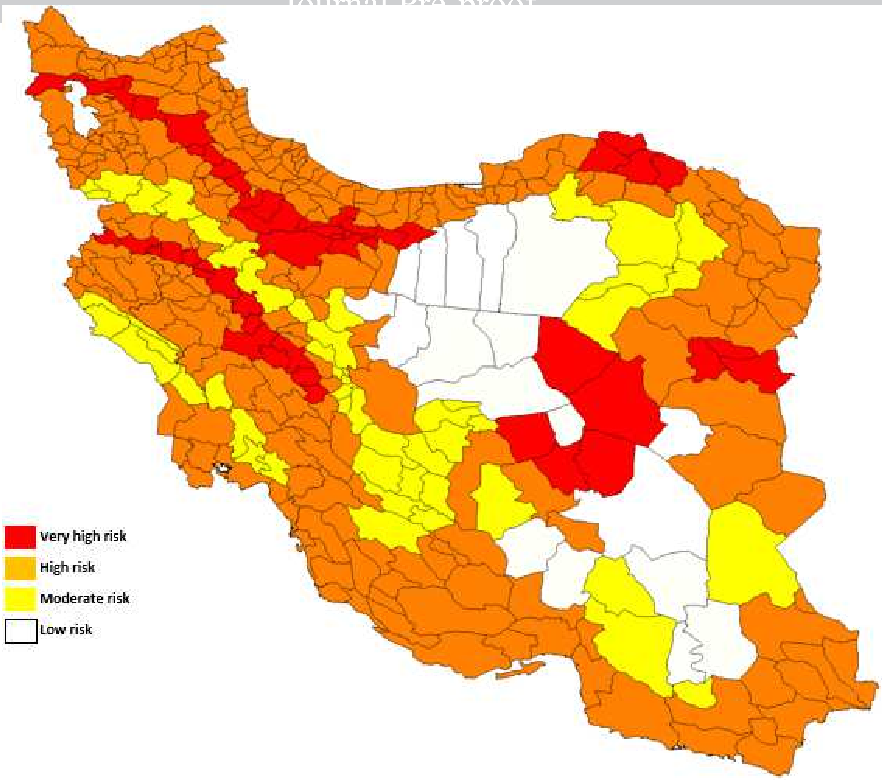


Fig. 4 (a). Approximate earthquake hazard zoning map of Iran

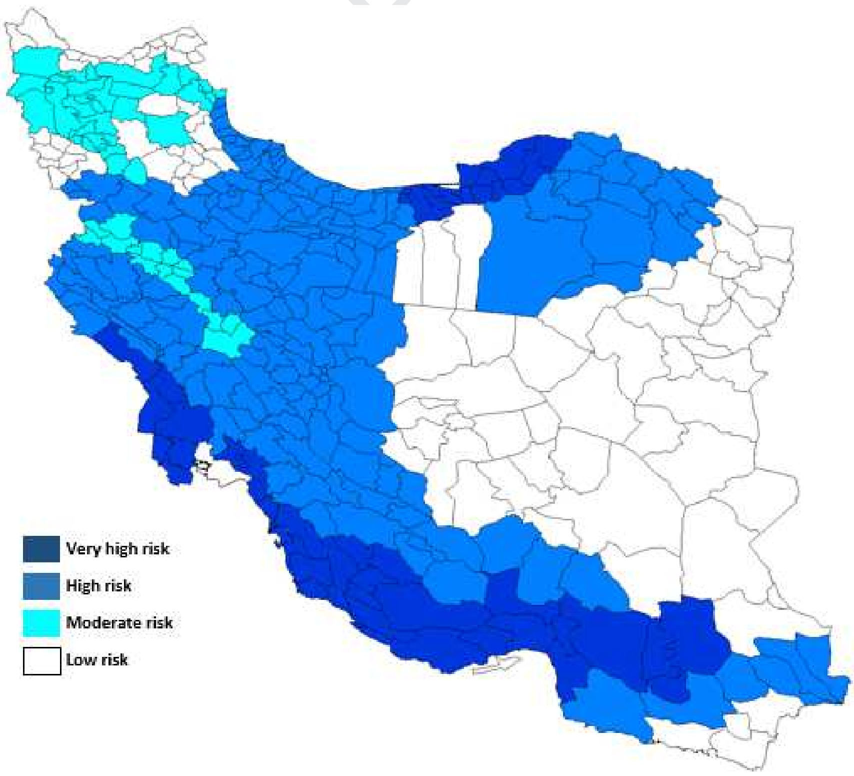


Fig. 4 (b). Approximate flood hazard zoning map of Iran

We apply the SAA method in the case example to show the CIs for lower and upper bounds of the true optimal objective value. For solving the case example, the parameters of the SAA method are set as K = 40, M = 10, K'=400. The resulting 95% CIs for the lower and upper bounds are presented in

Table 3. The percentage gap between the lower and upper ends of the CI related to the true optimal objective in (26) is reported in the last column of **Table 3**. It should be mentioned that in this sub-section parameter β is set to 1.

Table 3. Results from the SAA method for the case example

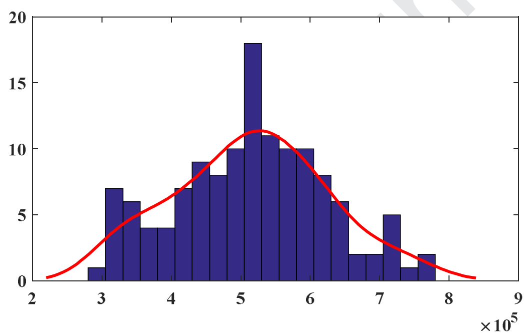
μ_U	CI for LB	CI for UB	Gap (%)
1.6787E+6	(1.6393, 1.6673) $\times 10^6$	(1.6646, 1.6928)$\times 10^6$	3.2%

5-3- the applicability of the resilience metric

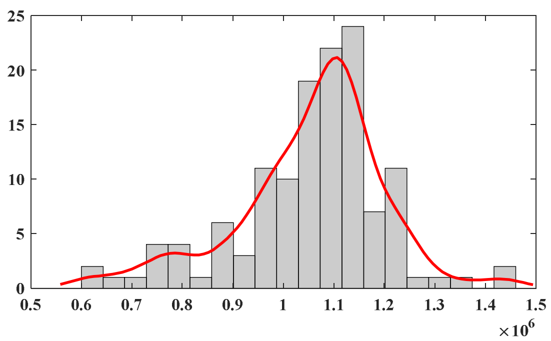
To emphasize the importance of the considered resilience metric. We solve the problem without considering the second stage problem ($\beta=\varepsilon,\ \ \varepsilon$ is a small number). Then, by using the simulation, we examine the solution of the case example with $\beta=1$ and $\beta=\varepsilon,$ for a set of disruption scenarios including 150 scenarios. The comparison between the SC costs is presented in **Table 4**. Further, in **Fig. 5**, the frequency of the SC cost increase in the face of disruptions is illustrated for these solutions.

Table 4. Comparison of the SC cost with and without the resilience metric consideration

	First stage cost: Total yearly SC cost	Simulation results	
		Resilience metric	Expected of recovery cost
$\beta=\varepsilon$	1.1743E+6	1.0537E+6	8.5092E+5
$\beta=1$	1.2146E+6	5.1425E+5	4.0114E+5



$\beta=1$



$\beta=\varepsilon$

Fig. 5. the frequency of SC cost increase that is obtained by simulation of the optimal solution with $\beta=1$ and $\beta=\varepsilon$.

As illustrated in **Table 4**, the first-stage objective of the problem that is the total yearly SC cost under normal condition increases about 3.4% by the disruption-driven design decisions. However, the resilience metric reduces 51.1% that highlights the main impact of our approach. The main importance of considering the resilience metric is also emphasized in **Fig 5**. In **Fig 5**, the average response of the SC cost increase during the recovery time for the case example with $\beta=1$ and $\beta=\varepsilon$ are 5.1425E+5 and 1.0537E+6, respectively. It should be mentioned that the SC's recovery cost takes about 80% of the resilience metric in this case example.

In the optimal design decisions from solving the case example with $\beta=1$ and $\beta=\varepsilon$, the number of established DCs are 28 and 24, and the total installed capacity are 94100 and 119193, respectively. Therefore, we can conclude that by considering the proposed resilience metric in the design phase, the average capacity of the established DCs decreases from 4966.3 to 3360.7. We can conclude that for the resilient SCND, it is not necessary to install more capacity for responding to customers in some cases. In our case study, in the design phase without consideration of the resilience metric, the SC benefits from the economy of scale related to the cost of opening facilities with high capacity.

The SAA method by setting K = 40, M = 10, and K'=400 is used for solving some generated problem instances and the above-mentioned analysis are done for them and the results are illustrated in **Table 5**. In **Table 5**, the percentage gap between the lower and upper ends of the CI related to the true objective in relation (26) is also reported.

Table 5. The impact of SC resilience metric consideration on design decisions by using simulation

Test instances	$\beta=\varepsilon$			$\beta=1$		
	Total yearly SC cost under normal condition	Resilience metric	SAA Gap (%)	Total yearly SC cost under normal condition	Decrease of resilience metric	SAA Gap (%)
P3	6.87E+05	4.36E+05	1.98 %	7.08E+05	41 %	2.14 %
P6	1.21E+06	8.92E+05	2.45 %	1.25E+06	51 %	2.87 %
P9	1.94E+06	1.01E+06	2.44 %	2.01E+06	49 %	3.09 %
P12	2.72E+06	1.69E+06	3.19 %	2.81E+06	54 %	3.37 %

The reported results in **Table 5** confirm the obtained results corresponding to the case example. Further, the presented gaps of the SAA approach in various test instances shows its acceptable performance and robustness. In **Fig. 6**, it is shown how the consideration of the resilience metric in the SCND decreases the expected increase of SC operational costs because of a disruption event and increases the yearly SC costs under normal condition in several problem instances. Based on **Fig. 6**, we can conclude that the increase of yearly SC costs is negligible in compared with the improvement of the SC's resiliency.

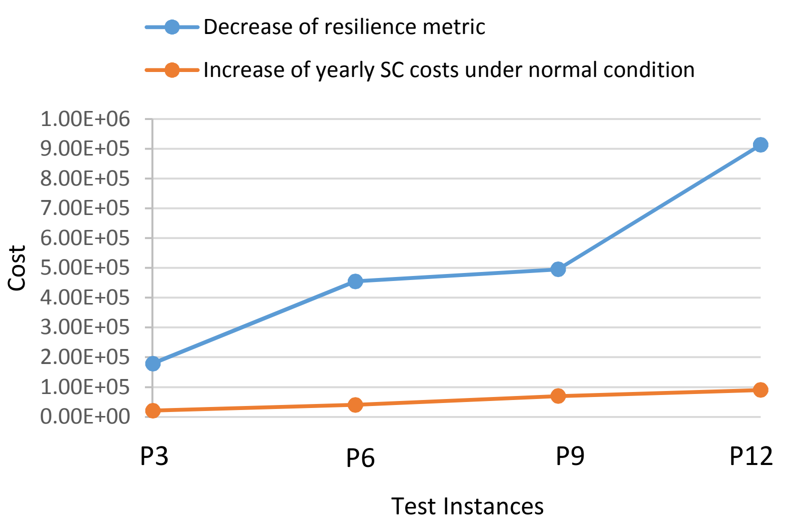


Fig. 6. Decrease of the resilience metric and increase of the yearly SC costs by using disruption-driven model.

In our optimization problem, about 75% of the SC cost increase is associated with the SC recovery and hence the recovery cost of SC network during its recovery period has a meaningful impact on the SC planning subject to disruption events. For designing a resilient SC, selection of reliable facilities has priority and the installed capacity of unreliable facilities with high likelihood of disruption should be reduced.

5-4- sensitivity analysis

A discussion related to the impact of main parameters' value on the solution of the stochastic program is presented in this sub-section.

Analysing the impact of parameter β: Parameter β in our stochastic program should be set by the decision maker, and illustrates the importance weight of the proposed resilience metric. To find how the total yearly SC cost and resilience metric change by considering various values for this parameter, the sensitivity analysis is done. **Fig 7** shows the sensitivity of the total yearly SC cost under normal condition (the first stage cost) to the value of parameter β in the case example. Furthermore, in **Fig 8**

, it is shown that in the case example, how the expected value and variability of the SC cost increase due to a disruption event change by considering various important weights for the resilience metric in the design phase.

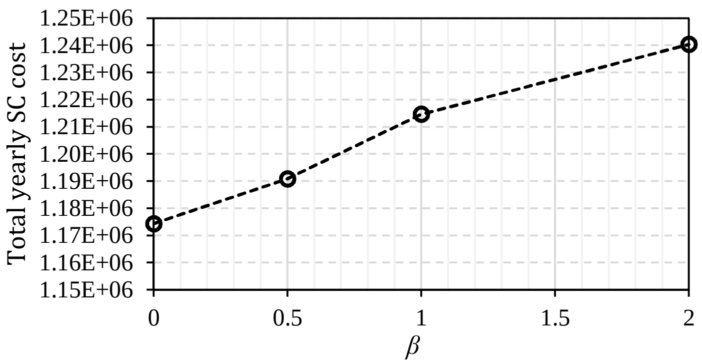


Fig. 7. the sensitivity of the first stage cost to parameter β

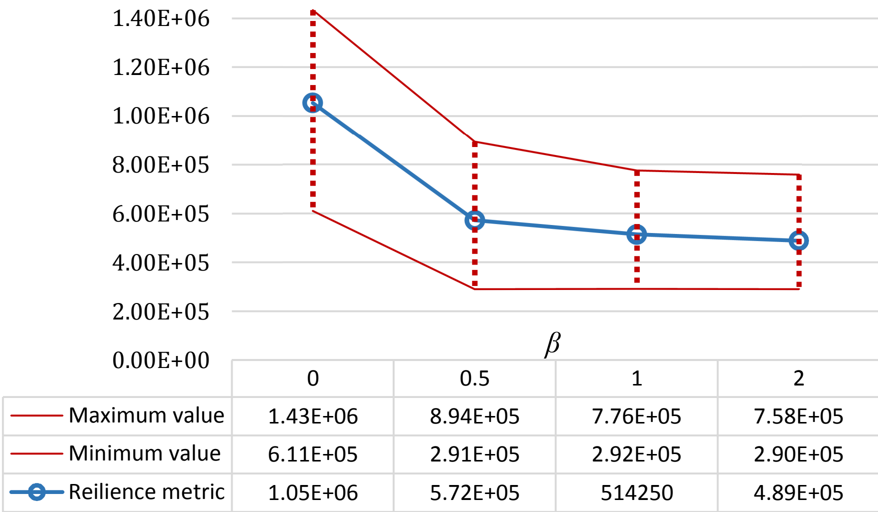


Fig.8. the sensitivity of the expected and variability of SC cost increase after a disruption event to parameter β

In **Fig. 8**, it is shown that our proposed approach for disruption-driven SCND reduces the SC cost increase in terms of the expected value and variability. Further, based on **Figs 7** and **8**, when we apply our approach for designing resilient SCs, the increase of the total yearly SC cost in compared with the decrease of the resilience metric is not significant. Therefore, we can highlight the applicability our proposed resilience metric for the SCND.

Analysing the impact of the recovery time: Based on the definition of the resilience as the ability to quickly and effectively recover from a disruption, the recovery time has a main role in the presented resilience metric. In **Table 6**, we report the impact of the recovery time value on the total yearly SC cost (the first stage cost) to obtain a resilient SC with $\beta=1$. The changes of the recovery time are exerted by multiplying some coefficients to this parameter. In **Table 6**, the main importance of the recovery time on the resilience metric is highlighted, and hence decision makers should develop recovery plans to return a disrupted SC to its initial state as soon as possible.

Table 6. the sensitivity of the SC costs to the recovery time

Problem instances		Multiplier coefficient for SC recovery time			
		0.1	**0.5**	**1**	**2**
Case example	The first stage cost	1.18E+06	1.20E+06	1.21E+06	1.21E+06
	Resilience metric	4.31E+05	4.69E+05	5.04E+05	5.38E+05
	Total Objective function	1.61E+06	1.67E+06	1.71E+06	1.75E+06
Problem instance 3	The first stage cost	6.90E+05	6.95E+05	6.99E+05	7.01E+05
	Resilience metric	2.01E+05	2.11E+05	2.16E+05	2.29E+05
	Total Objective function	8.91E+05	9.06E+05	9.15E+05	9.30E+05
Problem instance 5	The first stage cost	1.36E+06	1.37E+06	1.37E+06	1.37E+06
	Resilience metric	4.03E+05	4.52E+05	4.60E+05	5.04E+05
	Total Objective function	1.76E+06	1.82E+06	1.83E+06	1.87E+06

5-5- The effect of the risk-based resilience metric

The proposed resilience metric is based on the SC cost increase during the recovery period after a disruption event, and this cost for a SC network is stochastic and dependent on disruption scenarios. We have considered the expected value of the SC cost increase to introduce the resilience metric. In this sub-section, CVaR is applied to obtain the resilience metric and their impacts are investigated in three small-sized examples. It should be mentioned that the CVaR can be calculated in a stochastic program by linear programming techniques (Ahmed, 2006).

We can obtain $CVaR_{\alpha}(IC)$ instead of $\sum_{k\in K}\pi(k)IC(k)$ in objective (15) as follows (Govindan and Fattahi 2017):

$$\begin{aligned}
&CVaR_{\alpha}(IC)=\min:\eta+\frac{1}{1-\alpha}\left(\sum_{k\in K}\pi(k)\theta(k)\right),\\
&st.\\
&\theta(k)\geq IC(k)-\eta \quad \forall k\in K,\\
&\theta(k)\geq 0 \qquad\qquad \forall k\in K,\\
&\eta\in \mathbb{R}.
\end{aligned}$$

where, the possible loss for each scenarios *k* is illustrated by decision variable $\theta(k)$.

By the proposed risk-based resilience metric, we have solved three small-sized problem instances with 40 scenarios, $\beta=1$, and $CVaR_{0.95}$. Next, obtained design decisions are simulated for 100 disruption scenarios and the results are reported in **Table 7**.

Table 7. simulation results from solving problem instances with risk-based resilience metric

Problem instance	Resilience metric	Statistics of the resilience metric's simulation		
		mean	Standard deviation	75% quantile (QT)
P3	$CVaR_{0.95}$ measure	2.76E+5	2.01E+4	2.88E+5
	Expected value measure	2.59E+5	3.15E+4	2.92E+5
P5	$CVaR_{0.95}$ measure	4.77E+5	5.59E+4	5.08E+5
	Expected value measure	4.41E+5	7.66E+4	5.11E+5
P6	$CVaR_{0.95}$ measure	5.01E+5	5.02E+4	4.98E+5
	Expected value measure	4.40E+5	7.26E+4	5.03E+5

We can conclude from the simulation results that the risk-based resilience metric makes the expected value of the SC cost increase worse. On the other hand, it reduces the standard deviation and 75% QT of the SC cost increase because of a disruption event during its recovery time.

5-6- Analyzing different disruption scenarios

In this study, the increase of yearly SC cost (the first stage cost of our optimization model) after consideration of the resilience metric can be interpreted as the cost of designing a resilient SC network, called resilient design cost. However, the resilient design cost of SCs is dependent on the disruption risk of DCs and the percentage of unreliable potential DCs in the SCND problem. To highlight this issue, in this sub-section, we define three conditions and run several test instances with 40 scenarios under these conditions and in **Fig. 9** the percentage increase of the resilient design cost is reported for these problem instances under these conditions.

Condition 1: the probability of disruption occurrence at unreliable DCs is multiplied by 1.5.

Condition 2: the number of unreliable potential DCs is increased 15%.

Condition 3: both conditions (1) and (2) are considered.

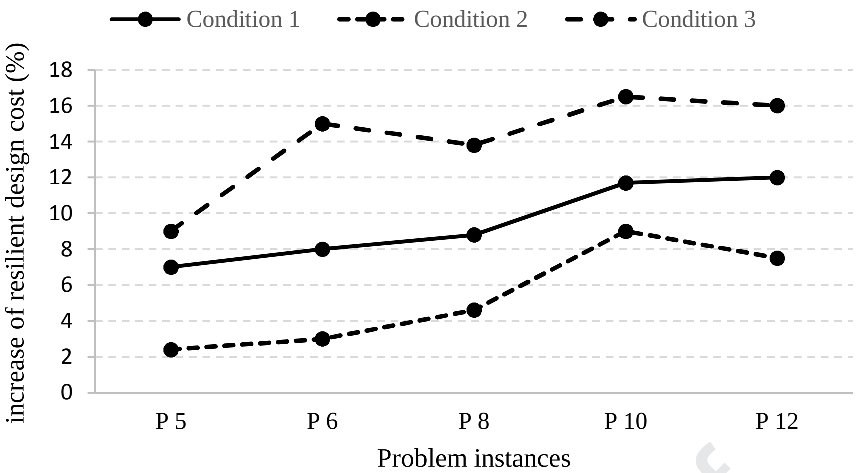


Fig.9. The impact of DCs' disruption risk and the percentage of unreliable potential DCs on resilient design cost

Presented results in **Fig. 9** highlight the meaningful impact of unreliable DCs' number and their disruption risk in designing resilient SC networks. As it is expected, by increasing the disruption probability and number of unreliable DCs in the SCND problem, the resilient design cost increases and the impact of disruption probability is more than the number of unreliable DCs in our study. It should be mentioned that the modelling approach of disruption impacts on SC networks has a main influence on design decisions.

6- Managerial implications

In this study, we address a main challenge corresponding to the quantification of a resilience metric for SC planning under disruption events. Although many studies (see survey papers related to this area such as Klibi et al., 2010; Snyder et al., 2016; Ivanov et al., 2017; Govindan et al., 2018) attempted to design SCs under disruption risk, most of them (e.g., Sheffi, 2005; Azad et al., 2013; Hasani and Khosrojerdi ,2016; Fattahi et al., 2017; Fattahi and Govindan, 2018; Jabbarzadeh et al., 2018) neglected the cost and time of the SC recovery after a disruption event and concluded that the establishment of more capacity in the design phase would lead to a resilient SC network. We formulate a new resilience metric that captures these two main aspects of SC disruptions, and we show computationally that in some situations, the establishment of excess capacity may lead to the increase of the SC's recovery cost. The main impacts of the SC's recovery time and cost on design decisions are also investigated. Furthermore, this study confirms the results of the literature (e.g., Mak and Shen, 2012; Hasani and Khosrojerdi, 2016) that states the increase of facilities' dispersion leads to the SC's resiliency. In practice, many companies, such as Toyota, Honda, BMW, and Intel, devote a significant attempt to obtain resiliency in the face of disruption events by quantitative models (Handfield et al., 2006). This study introduces a new applicable approach in this area that can be simply modified based on various SC planning problems.

The proposed two-stage stochastic program finds that second stage decisions should be made after a disruption event as corrective decisions. This approach enables us to develop a contingent planning based on a disruption scenario. This issue is scarcely addressed (see Tomlin, 2009; Fattahi et al., 2017) in the literature and our decision-making framework employs the contingent sourcing strategy that meaningfully reduces the SC's performance loss because of disruption events.

We investigate differences between the robust design of SCs under disruption risk and resilient-based objectives. Many robust design methods (e.g., Klibi and Martel, 2013; Baghalian et al., 2013; Jabbarzadeh et al., 2018) are criticized for obtaining over-conservative solutions based on the worst-case scenario. Contrary to this approach, our computational results highlight the proposed resilient-based objective, so the loss of the SC's efficiency in comparison with the increase of its resiliency is negligible. To improve the SC resilience metric by 50%, the average increase of the resilient design cost is less than 5%; this impressive outcome highlights the applicability of the proposed resilience metric. Further, our approach for designing resilient SCs allows for considering different risk attitudes of a decision maker by carefully adaption of control parameter β.

The SC cost increase due to a disruption event is a stochastic variable that is dependent on the SC network structure and on the severity and type of the disruption event. The resilience metric is quantified based on the expected SC cost increase in the face of a disruption event during its recovery time. This approach can help SC decision makers to find how the existing SC network is resilient under various disruption scenarios. We have shown the quantification approach of the resilience metric affects design decisions. The CVaR of the SC cost increases, in the face of a disruption event, is also investigated as a risk-based resilience metric. Computational results illustrate the risk-based metric leads to higher mean and lower variance and 75% QT in the distribution of the SC cost increase after a disruption event.

Based on computational results, network structure influences the impacts of a disruption on the SC. In many problem instances, to design a resilient distribution SC network, it is more favourable to increase the number of active DCs and to decrease the total established capacity. In sub-section 5-2, the resilient design for the problem instance presented (based on the Iran map) results in increasing the number of active DCs from 24 to 28 and decreasing the total installed capacity about 21%.

The occurrence of disruption events in a SC network may result in a ripple effect; further, many SC facilities may be simultaneously disrupted. This study proposes an applicable framework for the detection and construction of disruption scenarios based on the SAA approach that can address this issue. In addition, by this framework, a large number of disruption scenarios can be considered for modeling the uncertainty induced by disruption events without approximation of the scenarios' probability.

7- Conclusion

In the related literature, there exist a few metrics for the SC resilience, and these metrics are not suitable to be embedded in SC optimization models. In this paper, we propose a new metric for the SC resilience and use this metric in the design phase of a distribution SC network. We consider that the disruption events lead to the failure of unreliable facilities in the network and a two-stage stochastic program is developed. In the stochastic program, the resilience metric is formulated by minimizing the expected value of the SC cost increase during its recovery time after the realization of a disruption event.

The considered problem is initially formulated as a mixed-integer nonlinear problem, and then reformulated as a CQMIP, which is solvable by commercial solvers such as CPLEX. A particular emphasis of this paper has been put on the real-world applicability of the proposed resilience metric. To deal with a large number of disruption scenarios, the SAA method is employed. We test the validity of our model and the impact of the resilience metric consideration by using a simulation approach.

In the experimental results, we show the computational tractability of the proposed model by using several generated problem instances and a case example based on Iran geographical area. Furthermore, we investigate the impact of the recovery time and the resilience metric weight in our stochastic program on the optimal design solution, total yearly SC cost under normal condition, and the value of the resilience metric. Finally, we examine the risk-based resilient metric by using CVaR in some small-sized problem instances.

This paper presents a new resilience metric, and there are many opportunities to consider this metric in other SC optimization problems. Further, an interesting future work related to our problem is to extend the presented model for a multi-period SCND problem by using the multi-stage stochastic programming (see Fattahi et al. 2018).

Big data analytics, Industry 4.0 applications, and ERP systems can increase the SC's resilience in the pre- and post-disruption stages of the SC planning by real-time monitoring. Further, the big data analytics can help in the detection of disruption scenarios for designing resilient SC networks. As a consequence, the extension of the proposed optimization approach and resilience metric for digital technology applications is a promising future research direction.

Appendix A

Table A1. Generation of parameters in problem instances

Symbol	Value	Symbol	Value

$e_{i,j,p}$	$:U[1,30]$	$b_{i,n}$	$D=\sum_{j\in J}\sum_{p\in P}\mu_{jp}, b_{i,1}=\frac{D}{2\|I\|}\times U[0.9,1.2], b_{i,2}=\frac{D}{\|I\|}\times U[0.9,1.2], b_{i,3}=\frac{1.5D}{\|I\|}\times U[0.9,1.2], b_{i,4}=\frac{2.5D}{\|I\|}\times U[0.9,1.2]$
h_{ip}	$:U[5,8]$		
d_{ip}	$:U[12,18]$	$f_{i,n}$	$f_{i,1}=b_{i,1}\times 4\times U[2,2.25], f_{i,2}=b_{i,2}\times 4\times U[1.7,2], f_{i,3}=b_{i,3}\times 4\times U[1.4,1.7], f_{i,4}=b_{i,2}\times 4\times U[1.1,1.4]$
Lt_{ip}	$:U[3/300,8/300]$	$o_{i,n}$	$o_{i,1}=b_{i,1}\times U[0.9,1], o_{i,2}=b_{i,2}\times U[0.8,0.9], o_{i,3}=b_{i,3}\times U[0.7,0.8], o_{i,4}=b_{i,2}\times U[0.6,0.7]$
g_{ip}	$:U[10,15]$	$T(k)$	$U\left[\frac{50}{300},\frac{140}{300}\right]$
s_{ip}	$:U[4,10]$	rc	$4\times U[1,2]$
α, z_{α}	97.5%, 1.96	μ_{jp}	$:U[300,800]$
l_p	$:U[20,35]$	${\sigma_{jp}}^2$	$:U[10,40]$

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Author Contribution Statement

Equally contributed by all authors