

Resilient Supply Chain Under Risks: A Network and Structural Perspective

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Abstract

Constant development and change in the supply chain lead the system to meet various risks. Thus, a proper procedure should be adopted to cope with such issues. This study addresses a bi-objective model to design a resilient and robust forward supply chain under uncertainty and multiple disruptions. The investigated objective functions include minimizing the total cost and the total non-resiliency of the network, which is tackled using the ϵ -constraint method. Notably, resilience strategies and two-stage stochastic programming are respectively considered to cope with disruption and operational risks. Ultimately, some random numerical benchmarked examples are applied to the model to confirm the proposed formulation's performance. The results indicate that considering risks in the system leads to increased costs, but it would be profitable in the long term. Notably, a resilient chain can prevent system failure and enhance capabilities to reduce risk exposure costs and damages.

Keywords: Resilient supply chain, Network non-resiliency, Stochastic programming, Disruption, Operational risk

1. Introduction

A supply chain (SC) is a network consisted of various facilities, including suppliers, manufacturing centers (MCs), distribution centers (DCs), collection centers (CCs), transfer points (TPs), recycling centers (RCs), landfills, and customer zones (CZs) (Zhen et al., 2016). These components are often interconnected or intended for two significant purposes. The first is to receive raw materials, processing and transforming them into end products, and ultimately distributing products to CZs (forward flow), while the second regards collecting end of life products, disassembling parts, recycling reusable components, and finally distributing them to market zones (reverse flow). Note that facility location-allocation decisions significantly impact the performance of both forward and reverse SCs (Hajiaghaei-Keshteli & Fard, 2019). Hence, supply chain management (SCM) includes the systematic management of material, labor, financial, and information flows between the nodes of the network to optimize the total cost (TC) and customer service level simultaneously (Sabouhi & Jabalameli, 2019).

Risk in the planning of the SC includes uncertainty and disruption that can lead to system failure, and a long planning horizon can exacerbate it. The operational risk or uncertainty

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arising from supply and demand coordination problems known as the usual risk in SC has systemic and environmental origins (Nemati et al., 2017; Shi, 2004; Zhao & Ke, 2019). The disruption risks are associated with natural disasters, terrorist attacks, human errors, economic disorders, etc. Note that risks significantly reduce network reliability, so a systematic mechanism should be adopted to deal with it (Sreedevi & Saranga, 2017). Measures to counter the disruption risk are SC resilience (SCRES) strategies, including preventive and contingency (mitigation) techniques that lead to a resilient network (Adobor, 2019; Machado et al., 2018; Pettit et al., 2019). Preventive strategies are measures that organizations take before the disruption to achieve readiness for preventing losses and system failure. Mitigation or contingency strategies are performed after disruption to compensate for damages and return to a desired or better state. For example, flexible suppliers with instant capacity increases are critical elements in implementing mitigation strategies (Adobor, 2019; Tomlin, 2006). Therefore, SCM must identify, evaluate, and classify all possible disruption risks to take necessary and vital measures to prevent or mitigate risks in the business environment and achieve competitive advantages.

Based on the previous discussions, SC's resilience is a framework to wisely decrease the probability of failure and its consequences during the operational recovery for achieving regular performance and state. SC resilience includes different strategies and measures to diminish the destructive impacts of disruption risks on SC. SCM must take precautionary measures, such as providing backup facilities, multiple sourcing, fortification of facilities, and network resiliency (Adobor, 2019; Elluru et al., 2019; Hosseini et al., 2019). Therefore, the resilient supply chain network design (RESCND) has been an attractive research field in the latest relevant studies.

This study aims to enrich the relevant literature in the field of RESCND in several directions. First, partial facilities disruption and complete link disruptions are simultaneously considered in the proposed model, which is rarely considered in previous studies. Second, this study addresses a hybrid framework based on structural and network resilience measures to design resilient and responsive SC. Besides, contingency and precautionary planning approaches are concurrently applied in the proposed model. Third, a significant number of resilience strategies have been employed in this study, which leads to an increase in the flexibility and responsiveness of the concerned SC in the situation of disruption. Ultimately, this study addresses routing decisions to improve transportation time in the condition of disturbances.

This research aims to address some questions as follows. How should we design and implement quantitative resilience strategies? What are the advantages of a resilient network in SC? How reducing the total non-resiliency of the network (TNRN) influences the TC? What is the effect of altering facilities' capacity on objective functions (OFs)? How should we validate the proposed model? We applied the proposed model to three randomly generated datasets to answer these questions.

The content of this research is respectively organized as follows. In Section 2, related studies on the RESCND under risk are reviewed. Section 3 describes the problem, and in Section 4, the corresponding formulation is presented. Section 5 investigates the conversion of the two-stage bi-objective problem into a single-objective formulation. In Section 6, we applied three randomly generated datasets to the proposed robust formulation and extracted the computational results. Eventually, obtained conclusions along with directions for further researches are provided in Section 7.

2. Literature Review

The relevant studies in RESCND focus on various preventive and mitigation strategies to reduce the disastrous impacts of different SC disruptions. The main strategies include facility

fortification (FF), multiple sourcing (MS), network resiliency (NR), maintaining safety stock (MSS), holding pre-positioned emergency inventory (HPEI), and providing backup facilities (PBF). For instance, Azad et al. (2013) presented a RESCND under the disruption risk of DCs and transportation links. They utilized backup facilities and fortification strategies to weaken the harmful impacts of disturbance risks.

Garcia-Herreros et al. (2014) presented a model for RESCND under disruption considerations. They considered complete disturbance risks of facilities. In addition, they applied two-stage stochastic programming (TSSP) to counter threats. Nooraie and Parast (2016) designed a resilient SC under partial disruption of facilities and investigated several mitigation resiliency strategies, including multiple sourcing and providing backup facilities. Zahiri et al. (2017) presented a RESCND in a pharmaceutical company under operational and disruption risk taking into account sustainability dimensions. They also implemented a robust optimization (RO) method to deal with uncertainty. Ghavamifar et al. (2018) proposed RESCND under the risks of disturbance in a competitive environment. They considered complete disruptions of facilities and took some resilience strategies. Diabat et al. (2019) presented a RESCND considering facilities' reliability and disturbance risks. They applied robust stochastic programming along with utilizing multi-criteria decision making.

Pavlov et al. (2019) proposed an integrated model for RESCND by considering contingency and proactive measures and fortifying the network with redundancy. They also took into account sustainability conditions and resource constraints under structural dynamics. Rahimi et al. (2019) discussed risk-averse RESCND with quantity discounts under multiple disruptions. They also considered social and environmental issues to follow the sustainability aspects of SC. Besides, they considered the inherent uncertainty of the discussed problem caused by business fluctuations and market changes via a risk-averse method. Dehghani Sadrabadi et al. (2020) developed a robust model for the RESCND problem in the situation of simultaneous disruptions and operational risks. They applied the proposed formulation to an automotive real-life case study to ensure the model's validity and applicability. This study considered some measures including robustness, flexibility, agility, and redundancy to evaluate the resilience of investigated SC. In this research, Green SC principles and measures are prioritized using multi-criteria decision making (MCDM) methods.

Siar and Roghanian (2020) redesigned a resilient hybrid closed-loop SC under operational risks and disturbances by considering precautionary resilience strategies. They applied a robust possibilistic programming approach to cope with the inherent uncertainty of associated parameters. This study also tried to simplify the solving process by employing a Lagrangian relaxation method. Tucker et al. (2020) investigated designing a resilient SC to prevent pharmaceutical items shortage via a precautionary planning approach. They also employed stochastic programming to tackle operational risk. Yan and Ji (2020) discussed RESCND considering simultaneous uncertainty and disruptions. They applied uncertain programming to manage disorders and risks in a multi-echelon SC to satisfy customers' demands and achieve the minimum cost simultaneously. In addition, in this study, a Lagrangian relaxation method is applied to simplify the solving process.

Sabouhi and Jabalameli (2019) designed a resilient SC in the situation of disruption risk. This study efficiently employed some measures to minimize the network's non-resiliency and the TC of risk exposure. Hosseini-Motlagh et al. (2020) extended a resilient food SC considering network resiliency strategies. They developed a framework to optimize SC in terms of TC, TNRN, and sustainability's social dimension. The proposed model was capable of considering the network resiliency measures. Most of the reviewed studies just utilized

mitigation and preventive strategies to design resilient SC against disruption risks. Notably, most organizations are intending to maximize the network resiliency along with minimizing the total system cost. Network resiliency is a new field of study in the area of RESCND that has several components. According to relevant studies, network density (ND), flow criticality (FCr), flow complexity (FC), node criticality (NCr), and node complexity (NC) represent measures for the non-resiliency of the network. Note that Hosseini-Motlagh et al. (2020), Sabouhi and Jabalameli (2019), and Zahiri et al. (2017) are the only studies discussed enhancing the resilience capabilities of SC via minimizing the non-resiliency of the network.

Table 1 illustrates the characteristics of reviewed relevant studies in the area of the RESCND problem. It should be noted that the main criteria for reviewing researches include disruption specifications, type of resilience strategies, and uncertainty approach.

		Reference	Azad et al. (2013)	Dehghani et al. (2020)	Diabat et al. (2019)	Garcia-Herreros et al. (2014)	Ghavamifar et al. (2018)	Hosseini-Motlagh et al. (2020)	Mohammed et al. (2019)	Nooraie & Parast (2016)	Pavlov et al., 2019)	Rahimi et al. (2019)	Sabouhi & Jabalameli (2019)	Siar & Roghanian (2020)	Tucker et al. (2020)	Yan & Ji (2020)	Zahiri et al (2017)	This paper
		Partial		\checkmark			\checkmark	✓				\checkmark	\checkmark	\checkmark	\checkmark			*
-		Complete		\checkmark	\checkmark				√							✓	✓	*
tioı	Type	Single		,	,		,	,	\checkmark			,	,	,	,	✓	\checkmark	
ïca	É.	Multiple		~	~		\checkmark	\checkmark	,			√	\checkmark	\checkmark	\checkmark	v	,	*
ecif		Sequential		~		_			~	_		~				~	~	*
spe		Simultaneous			v		v				v		v	V	./	./		*
ion		Supplier Distribution		v				v				v			v	v		
Disruption specification	/el	center		✓	\checkmark		\checkmark					√		\checkmark			✓	*
Dis	Level	Production center		✓									\checkmark	\checkmark	\checkmark		\checkmark	*
		Transportation		\checkmark	\checkmark		\checkmark	\checkmark										*
Resilience strategies	Structural	Mitigation		✓	✓										~			*
trate	Strı	Precautionary			\checkmark		\checkmark	\checkmark				\checkmark		\checkmark		\checkmark		*
ce si	¥	Node complexity						\checkmark					\checkmark				\checkmark	*
ilien	Network	Flow																*
Ses	Ne	complexity						v					v				v	•
-		Node criticality						\checkmark					\checkmark				\checkmark	*
ty	-	Deterministic														\checkmark		
Uncertainty	approach	SP		,			\checkmark	√				\checkmark	\checkmark		\checkmark		√	*
ert	pro	FP		✓	,			√									\checkmark	
Jnc	ap	RO		✓	\checkmark			\checkmark						,				
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		lulti-stage		✓	•		✓	√				•	✓	✓	•		•	
SD.		ulti-period	D. E.	\checkmark	\checkmark			✓	tontin			✓	onorio		√		\checkmark	*

Table 1. Characteristics of Reviewed Relevant Studies in the Area of RESCND Problem

SP: Stochastic programming, FP: Fuzzy programming, RO: Robust optimization, SBR: Scenario-based robust

The research gaps are stated as follows. First, the relevant studies do not sufficiently address multi-echelon RESCND under disruption considerations. Second, mitigation and preventive resilience strategies have been rarely applied simultaneously in the literature of RESCND, and most relevant studies considered only one of these two types of resilience strategies. Third, only a few studies in RESCND have considered multiple risks of disturbance and simultaneous disruption in transportation links, facilities, and routes among them. Fourth, researchers do not pay much attention to lateral transshipment between facilities as a resilience strategy in the situation of disruption. Fifth, the reviewed studies rarely consider operational and disruption risks concurrently in the RESCND problems. Sixth, the reviewed studies in the area of RESCND do not widely discuss the network non-resiliency measures including, NC, NCr, FC, FCr, and network density.

According to the identified gaps, this study intends to enrich the literature in RESCND in several novel directions. To this aim, this study presents a bi-objective multi-echelon stochastic and resilient SC model to minimize the TC of SC and the TNRN simultaneously. The given system is exposed to multiple risks that disrupt different facilities, routes, and links. The usual operational risks arising from the inherent uncertainties in parameters and business environment fluctuations are considered. Notably, disruption scenarios are applied, and operational risks are tackled using TSSP simultaneously. In this study, contingency and preventive resilience strategies, including determining excess capacity, holding pre-positioned emergency inventory (EI), considering lateral transshipment, and multiple supplying are employed simultaneously. In addition, non-resiliency measures, including NCr, NC, and FC, are applied to design a resilient network. This work considers partially disrupted facilities, which means they lose only a certain percentage of the service capacity under each disruption scenario. It also considers complete concurrent disruption in transportation links and the routes among them. Unlike most of the reviewed studies, we applied structural resilience strategies and measures of the network non-resiliency to design a resilient network and assess the resiliency index. Note that the network non-resiliency measures include NC, NCr, FC, and FCr.

This study aims to make the following strategic and operational decisions by solving the proposed model. The intended early decisions include locating RMSs, DEs, MCs, and DCs, determining the amount of product between facilities, and determining the number of lost sales products in markets. In addition, investigating the amount of pre-positioned emergency inventories that should be kept, determining the excess capacity of different facilities in the situations of disruptions, and specifying the amount of purchase from the pre-positioned inventory of facilities are considered as resilience decisions.

3. Problem Description

This study presents the network design of a resilient and robust SC under uncertainty and the risks of disturbance. The investigated model, which is multi-stage, multi-echelon, multi-product, and multi-period, is vulnerable to uncertainty and disturbance risks. As illustrated in Figure 1, a six-level forward SC consisting of RMSs, DEs, MCs, DCs, and product CZs is considered. The flow in the concerned SC is as follows. DEs receive raw materials from RMSs to transport them to MCs for manufacturing products. Then, MCs transmit authorized products to DCs. Eventually, DCs deliver products to CZs. It is assumed that the risks of disturbance disrupt the facilities, routes among them, and the transportation links simultaneously in the investigated SC. Accordingly, this work considers partial and complete disruption risks in facilities and transportation links, respectively. Notably, all possible disruptions that may take place in the SC are identified and defined using a set of independent

scenarios to illustrate the situation that each scenario will cause. The investigated disruption scenarios are such that if a route is disrupted, transportation will be stopped through that route. Besides, this study applies a TSSP approach to counter the impacts of concerned disruption scenarios. This method involves the two-phase of decision-making, including preevent (first stage) and post-event (second stage). The pre-event stage involves strategic and scenario-independent decisions, while the post-event stage deals with operational and scenario-dependent decisions.

This work considers structural and network resiliency measures simultaneously to reduce the harmful impacts of disruption risks. Applied structural resilience strategies include multiple sourcing, determining excess capacity, holding pre-positioned inventory, and lateral transshipment. On the other hand, the TNRN is optimized, considering criteria NCr, NC, and FC. The inherent uncertainties in parameters and business environment fluctuations will cause operational risks in the proposed SC, so a systematic procedure must be applied to tackle these risks. Fortunately, a robust stochastic programming model is developed to counter operational risks and disruptions simultaneously. The model decisions include locating RMSs, DEs, MCs, and DCs, determining the amount of product or parts shipped among facilities, the amount of safety or pre-positioned inventory that should be held in different facilities, the amount of excess capacity for facilities in the situation of disruptions, and the amount of lost sale for products in market zones.

This study proposed a robust stochastic bi-objective multi-product model for the RESCND problem to achieve optimal decisions. The OFs include minimizing the TC of SC and TNRN. Note that the ε -constraint method is utilized to tackle multiple OFs.

Further assumptions are considered as follows:

- Facilities have limited capacities.
- Transportation between facilities can only take place using a single route.
- Candidate locations for opening RMSs, MCs, DEs, and DCs are known.
- Partial disruption on facilities and complete disruption for routes are considered in the situation of disturbance risks.
- Disruption scenarios occur independently and with a specified probability.
- Shortages in market zones are considered lost sales.

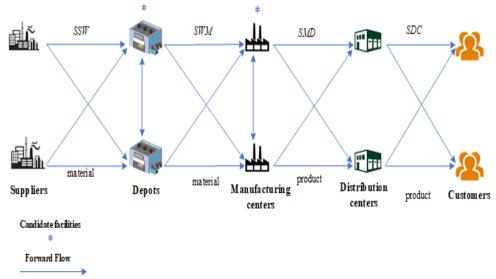


Fig. 1. Configuration of the Proposed Robust and Resilient SC

4. Model Formulation

The following indices, parameters, and decision variables are utilized to formulate the concerned SC in this research carried out from the stakeholder's perspective in the system. Note that all formulations are based on TSSP.

4.1. Notations

Sets:

DCIS.		
С	Index of products CZs	$c \in C$
D	Index of candidate locations for DCs	$d \in D$
Ι	Index of raw material families	$i \in I$
М	Index of candidate locations for MCs	m, m' \in M
Р	Index of products families	$p \in P$
S	Index of candidate locations for RMSs	$s \in S$
W	Index of candidate locations for DEs	w, w' \in W
R	Index of available routes	$r \in R$
0	Index of disruption scenarios	$o \in O$
Т	Index of periods	$o \in T$

Parameters:

EC_s, EC_w	The establishment cost of RMS s and depot w (million Rials)
EC_m, EC_d	The establishment cost of MC m and DC d (million Rials)
PC_{pmt}^{o}	The unit manufacturing cost of the <i>p</i> -type product at MC m in period t under scenario o (million Rials/ton)
DC ^o _{pdcrt}	The unit distribution cost of the <i>p</i> -type product by DC <i>d</i> to products CZ <i>c</i> by route <i>r</i> in period <i>t</i> under scenario o (million Rials /ton.km)
$HC^{o}_{iwt}, HC^{o}_{imt}$	The unit cost of holding <i>i</i> -type raw material at depot w and MC m in period t under scenario o (million Rials/ton)
SC^{o}_{pct}	The unit shortage cost of lost sales for the <i>p</i> -type product at products CZ c in period t under scenario o (million Rials/ton)
$TC_{iswrt}^{o}, TC_{iwmrt}^{o}$	The unit transshipment cost of <i>i</i> -type raw material from RMS <i>s</i> to depot <i>w</i> and depot <i>w</i> to MC <i>m</i> by route <i>r</i> in period <i>t</i> under scenario o (million Rials/ton.km)
TC ⁰ pmdrt	The unit transshipment cost of the <i>p</i> -type product from MC <i>m</i> to DC <i>d</i> by route <i>r</i> in period <i>t</i> under scenario o (million Rials/ton.km)
$TC^{o}_{iww'rt}$, $TC^{o}_{pmm'rt}$	The unit lateral transshipment cost of <i>i</i> -type raw material from depot w to depot w' and <i>p</i> -type product from MC <i>m</i> to MC m' by route <i>r</i> in period <i>t</i> under scenario <i>o</i> (million Rials/ton.km)
$VC_{ist}^{o}, VC_{iwt}^{o}$	The unit cost of excess transshipment capacity of <i>i</i> -type raw material at RMS s and depot w in period t under scenario o (million Rials/ton)
$VC^{o}_{pmt}, VC^{o}_{pdt}$	The unit cost of excess transshipment capacity of p -type product at MC m and DC d in period t under scenario o (million Rials/ton)
$HP_{ist}^{o}, HP_{pmt}^{o}$	The unit cost of holding pre-positioned EI of <i>i</i> -type raw material at fortified RMS s and p -type product at fortified MC m in period t under scenario o (million Rials/ton)
$BE^{o}_{iswt}, BE^{o}_{pmdt}$	The unit cost of providing <i>i</i> -type raw material from the EI of fortified RMS <i>s</i> by depot <i>w</i> or <i>p</i> -type product from the EI of fortified MC <i>m</i> by DC <i>d</i> in period <i>t</i> under scenario o (million Rials/ton)
DE_{pct}^{o}	The demand of p -type product at products CZ c in period t under scenario o (ton)
$d_{swr}, d_{wmr}, d_{mdr}$	The distance between RMS <i>s</i> and depot <i>w</i> , depot <i>w</i> and MC <i>m</i> , MC <i>m</i> and DC <i>d</i> by route r (Km)
$d_{dcr}, d_{mm'r}, d_{ww'r}$	The distance between DC d and CZ c , MC m and MC m' , depot w and depot w' by route r (Km)

$Cap_{ist}^{Tr}, Cap_{iwt}^{Tr}$	The transshipment capacity of <i>i</i> -type raw material at RMS s and depot w in period t (ton)
$Cap_{iwt}^{Ho}, Cap_{imt}^{Ho}$	The holding capacity of <i>i</i> -type raw material at depot w and MC m in period t (ton)
$Cap_{pmt}^{Tr}, Cap_{pdt}^{Tr}$	The transshipment capacity of p -type product at MC m and DC d in period t (ton)
Cap_{pmt}^{\Pr}	The manufacturing capacity of p -type product at MC m in period t (ton)
Cap_{pdt}^{De}	The delivery capacity of p -type product at DC d in period t (ton)
$MCap_{ist}^{o}, MCap_{pmt}^{o}$	The maximum holding capacity of pre-positioned EI for <i>i</i> -type raw material that can be held at fortified RMS <i>s</i> , and <i>p</i> -type product that can be held at fortified MC m in period t under scenario o (ton)
$RT_{ist}^{o}, RT_{iwt}^{o}$	The percentage of reduction in transshipment capacity of <i>i</i> -type raw material at RMS s and depot w in period t under scenario o (percentage)
RH^o_{iwt}, RH^o_{imt}	The percentage of reduction in holding capacity of <i>i</i> -type raw material at depot w and MC m in period t under scenario o (percentage)
$RT_{pmt}^{o}, RT_{pdt}^{o}$	The percentage of reduction in transshipment capacity of p -type product at MC m and DC d in period t under scenario o (percentage)
RP_{pmt}^{o}	The percentage of reduction in manufacturing capacity of p -type product at MC m in period t under scenario o (percentage)
RD_{pdt}^{o}	The percentage of reduction in the delivery capacity of p -type product at DC d in period t under scenario o (percentage)
$\omega^o_{swrt}, \eta^o_{wmrt}$	A binary parameter, equal to 1 if route r between RMS s and depot w , depot w , and MC m is disrupted in period t under scenario o ; 0, otherwise.
$\Psi^o_{mdrt}, \gamma^o_{dcrt}$	A binary parameter, equal to 1 if route r between MC m and DC d , DC d , and CZ c is disrupted in period t under scenario o ; 0, otherwise.
$\phi,\phi',\phi'',\phi'''$	The unit penalty coefficient of FC between RMS <i>s</i> and depot <i>w</i> , depot <i>w</i> and MC <i>m</i> , MC <i>m</i> and DC <i>d</i> , DC <i>d</i> and CZ <i>c</i>
μ,μ',μ'',μ'''	The unit penalty coefficient for NC of RMSs, depots, MCs, and DCs
heta, heta', heta'', heta'''	The unit penalty coefficient for critical RMSs, depots, MCs, and DCs
$ au_{so}^{NCr}, au_{wo}^{NCr},$	
$ au_{mo}^{NCr}, au_{do}^{NCr}$	NCr threshold for RMS <i>s</i> , depot <i>w</i> , MC <i>m</i> , and DC <i>d</i> under scenario <i>o</i>
δ_{ip}	The conversion factor of <i>i</i> -type raw material in <i>p</i> -type product (percentage)
λ	Variability weight
ξ	Risk aversion weight
BM	Sufficient large positive number
π_o	The probability of occurrence for scenario o

Decision Variables:

OS_s, OW_w	Represents 1 if RMS s or depot w is established; 0, otherwise.
OM_m, OD_d	Represents 1 if MC <i>m</i> or DC <i>d</i> is established; 0, otherwise.
SW ^o _{swrt} , WM ^o _{wmrt}	Represents 1 if depot w is allocated to RMS s or MC m is allocated to depot w by route r in period t under scenario o ; 0, otherwise.
$MD^{o}_{mdrt}, DC^{o}_{dcrt}$	Represents 1 if DC d is allocated to MC m or CZ c is allocated to DC d by route r in period t under scenario o ; 0, otherwise.
$CS_{s}', CW_{w}',$	Represents 1 if RMS s, depot w, MC m, or DC d is a critical node; 0, otherwise.
CM_{m}', CD_{d}'	
TA^{o}_{ipswrt} , TA^{o}_{ipwmrt}	The amount of <i>i</i> -type raw material of <i>p</i> -type product transmitted from RMS <i>s</i> to depot <i>w</i> , from depot <i>w</i> to MC <i>m</i> and from depot <i>w</i> to depot w' by route <i>r</i> in
$,TA^{o}_{ipww'rt}$	period t under scenario o (ton)

$TA^{o}_{pmdrt}, TA^{o}_{pmm'rt}$	The amount of p -type product transmitted from MC m to DC d , from MC m to
$,TA^{o}_{pdcrt}$	MC <i>m</i> ' and from DC <i>d</i> to CZ <i>c</i> by route <i>r</i> in period <i>t</i> under scenario <i>o</i> (ton)
PA ^o _{pmt}	The amount of p -type product manufactured at MC m in period t under scenario o (ton)
$IL^{o}_{ipmt}, IL^{o}_{ipwt}$	The inventory level of the <i>i</i> -type raw material of <i>p</i> -type product at MC m and depot w in period t under scenario o (ton)
LS_{pct}^{o}	The lost sale of the <i>p</i> -type product at CZ c in period t under scenario o (ton)
$ETC_{ist}^{o}, ETC_{iwt}^{o}$	The amount of incremented transshipment capacity of <i>i</i> -type raw material at RMS s and depot w in period t under scenario o (ton)
ETC^{o}_{pmt} , ETC^{o}_{pdt}	The amount of incremented transshipment capacity of p -type product at MC m and DC d in period t under scenario o (ton)
PEI ^o _{ipst}	The pre-positioned EI level of the <i>i</i> -type raw material of <i>p</i> -type product at RMS s in period t under scenario o (ton)
PEI ^o _{pmt}	The pre-positioned EI level of p -type product at MC m in period t under scenario o (ton)
PFE ^o _{ipswt}	The amount of <i>i</i> -type raw material of <i>p</i> -type product purchased by depot w from the EI of RMS <i>s</i> in period <i>t</i> under scenario o (ton)
PFE ^o pmdt	The amount of <i>p</i> -type product purchased by DC d from the EI of MC m in period t under scenario o (ton)

This study's modeling procedure is based on TSSP (Hamdan & Diabat, 2020), so the mathematical formulation is proposed as follows.

4.2. Network Non-Resiliency Measures

4.2.1. Flow Complexity

FC assesses the overall interaction between SC nodes. Increasing FC has a remarkable impact on SC complexity, causing complications and intricacy in the network (Zahiri et al., 2017). Consequently, SC's planning and management processes will be complicated, which leads to a substantial diminution in the system's ability to prevent or mitigate disruption risks that cause increasing the required cost and time for recovery and decreasing the retrieval quality. Eventually, such risks lead to destructive influences on network performance, result in financial losses, and bring about extreme system failures (Sabouhi & Jabalameli, 2019). Based on this measure, increasing the total interactions or links in SC causes network complexity. Equations (1)-(2) indicates the total considered links between the concerned SC nodes.

$$\sum_{(s,w,r,t,o)} SW^o_{swrt} + \sum_{(w,m,r,t,o)} WM^o_{wmrt} + \sum_{(m,d,r,t,o)} MD^o_{mdrt} + \sum_{(d,c,r,t,o)} DC^o_{dcrt}$$
(1)

$$SW^{o}_{swrt}, WM^{o}_{wmrt}, MD^{o}_{mdrt}, DC^{o}_{dcrt}, \in \{0,1\} \qquad \qquad \forall s \in S, \forall w \in W, \forall m \in M, \\ \forall d \in D, \forall c \in C, \forall r \in R, \\ \forall t \in T, \forall o \in O \end{cases}$$

$$(2)$$

4.2.2. Node Complexity

NC represents the total active nodes or opened facilities in SC. Technically speaking, the higher the number of active or opened facilities in the SC is, the more node complexity the

network has. The discussed measure is calculated using Equations (3)-(4) (Sabouhi & Jabalameli, 2019; Zahiri et al., 2017).

$$\sum_{s \in S} OS_s + \sum_{w \in S} OW_w + \sum_{m \in M} OM_m + \sum_{d \in D} OD_d$$
(3)

$$OS_s, OW_w, OM_m, OD_d \in \{0, 1\} \qquad \forall s \in S, \forall w \in W, \forall m \in M, \forall d \in D$$

$$(4)$$

4.2.3. Node Criticality

The amount of input and output flows to the SC node is an accurate indicator to assess NCr. In other words, if the total flows to a particular node of the system are higher than a specified threshold, that node is recognized as critical. Therefore, increasing the number of SC critical nodes leads to an increase in non-resiliency of the network and a reduction of the performance of system capabilities in the situation of disruption risk (Sabouhi & Jabalameli, 2019; Zahiri et al., 2017). Equations (5)-(9) indicate the critical nodes for RMSs, DEs, MCs, DCs, respectively.

$$CS_{s}' = 1 \left| \sum_{(i,p,w,r,t)} TA_{ipswrt}^{o} \ge \tau_{so}^{NCr} \qquad \forall s \in S, \forall o \in O$$
(5)

$$CW_{w}' = 1 \begin{vmatrix} \sum_{(i,p,s,r,t)} TA_{ipswrt}^{o} + \sum_{(i,p,w' \in W/\{w\},r,t)} TA_{ipw'wrt}^{o} \\ + \sum_{(i,p,s,t)} PFE_{ipswt}^{o} + \sum_{(i,p,m,r,t)} TA_{ipwmrt}^{o} \\ + \sum_{(i,p,w' \in W/\{w\},r,t)} TA_{ipww'rt}^{o} \ge \tau_{wo}^{NCr} \end{vmatrix} \quad \forall w \in W, \forall o \in O$$

$$(6)$$

$$CM_{m}' = 1 \begin{vmatrix} \sum_{(i,p,w,r,t)} TA_{ipwmrt}^{o} + \sum_{(p,m' \in M/\{m\},r,t)} TA_{pm'mrt}^{o} \\ + \sum_{(i,p,t)} \frac{PA_{ipm}^{o}}{\delta_{ip}} - \sum_{(p,m' \in M/\{m\},r,t)} TA_{pmm'rt}^{o} \ge \tau_{mo}^{NCr} \end{vmatrix} \quad \forall m \in M, \forall o \in O$$

$$(7)$$

$$CD_{d}' = 1 \begin{vmatrix} \sum_{(p,m,r,t)} TA_{pmdrt}^{o} + \sum_{(p,m,t)} PFE_{pmdt}^{o} \\ + \sum_{(p,c,r,t)} TA_{pdcrt}^{o} \ge \tau_{do}^{NCr} \end{vmatrix} \quad \forall d \in D, \forall o \in O$$
(8)

4.3. Objective Functions

4.3.1. Total Cost

The OF (10) ensures the minimization of the expected costs of SC under disruption scenarios. This term includes the costs of establishing new facilities $(TFOC_o)$, product transshipment

 (TTC_o) , product distribution (TDC_o) , manufacturing operations (TOC_o) , lost sales $(TSHC_o)$, and holding inventory (THC_o) as permanent costs. Besides, this OF entails structural resiliency cost consisting of the expenses of incremented capacity in disruption situation $(TECC_o)$, maintaining pre-positioned EI $(TPIC_o)$, and purchasing from the EI kept by fortified facilities $(TPEIC_o)$. Terms (11)-(19) define the components of the total SC costs.

$$Min \operatorname{Cos} t = \sum_{o \in O} \pi_o \begin{pmatrix} TFOC_o + TTC_o + TDC_o + TOC_o + THC_o \\ +TSHC_o + TPIC_o + TPEIC_o + TECC_o \end{pmatrix}$$
(10)

$$TFOC_o = \sum_{s \in S} EC_s OS_s + \sum_{w \in W} EC_w OW_w + \sum_{m \in M} EC_m OM_m + \sum_{d \in D} EC_d OD_d$$
(11)

$$= \left[\sum_{(i,p,s,w,r,t)} TC^o_{iswrt} TA^o_{ipswrt} d_{swr} + \sum_{(i,p,w,m,r,t)} TC^o_{iwmrt} TA^o_{ipwmrt} d_{wmr} + \sum_{ipwmrt} TC^o_{immrt} TA^o_{ipwmrt} d_{wmr} \right]$$

$$= \left[+ \sum_{i} TC^o_{immrt} TA^o_{immrt} d_{mdr} + \sum_{immrt} TC^o_{immrt} TA^o_{immrt} d_{wmr} \right]$$

$$(12)$$

$$TTC_{o} = \left(+ \sum_{\substack{(p,m,d,r,t) \\ (p,m,m' \in M/\{m\},r,t)}} TC_{pmdrt}^{o} TA_{pmdrt}^{o} d_{mdr} + \sum_{\substack{(i,p,w,w' \in W/\{w\},r,t) \\ (i,p,w,w' \in W/\{w\},r,t)}} TC_{ipww'rt}^{o} TA_{ipww'rt}^{o} d_{ww'r} \right)$$
(12)

$$TDCo = \sum_{(p,d,c,r,t)} DC_{pdcrt}^{o} TA_{pdcrt}^{o} d_{dcr}$$
(13)

$$TOC_o = \sum_{p \in P} \sum_{m \in M} \sum_{t \in T} PC_{pmt}^o PA_{pmt}^o$$
(14)

$$TSHC_o = \sum_{p \in P} \sum_{c \in C} \sum_{t \in T} SC_{pct}^o LS_{pct}^o$$
(15)

$$THC_o = \sum_{(i,p,w,t)} HC_{iwt}^o IL_{ipwt}^o + \sum_{(i,p,m,t)} HC_{imt}^o IL_{ipmt}^o$$
(16)

$$TECC_{o} = \begin{pmatrix} \sum_{(i,s,t)} VC_{ist}^{o} ETC_{ist}^{o} + \sum_{(i,w,t)} VC_{iwt}^{o} ETC_{iwt}^{o} \\ + \sum_{(p,m,t)} VC_{pmt}^{o} ETC_{pmt}^{o} + \sum_{(p,d,t)} VC_{pdt}^{o} ETC_{pdt}^{o} \end{pmatrix}$$
(17)

$$TPIC_{o} = \sum_{(i,p,s,t)} HP_{ist}^{o} PEI_{ipst}^{o} + \sum_{(p,m,t)} HP_{pmt}^{o} PEI_{pmt}^{o}$$
(18)

$$TPEIC_{o} = \sum_{(i,p,s,w,t)} BE_{iswt}^{o} PFE_{ipswt}^{o} + \sum_{(p,m,d,t)} BE_{pmdt}^{o} PFE_{pmdt}^{o}$$
(19)

4.3.2. Total Non-Resiliency of the Network

The OF (20) minimizes the total network non-resiliency of the concerned SC that consists of three terms, including FC, NC, and NCr, respectively. Note that section 4-2 thoroughly discussed the TNRN criteria.

$$TNRES = \begin{pmatrix} \sum_{(s,w,r,t,o)} \phi SW_{swrt}^{o} + \sum_{(w,m,r,t,o)} \phi'WM_{wmrt}^{o} \\ + \sum_{(m,d,r,t,o)} \phi''MD_{mdrt}^{o} + \sum_{(d,c,r,t,o)} \phi'''DC_{dcrt}^{o} \end{pmatrix} + \begin{pmatrix} \sum_{s} \mu OS_{s} + \sum_{w} \mu' OW_{w} + \sum_{m} \mu'' OM_{m} + \sum_{d} \mu''' OD_{d} \end{pmatrix} + \begin{pmatrix} \sum_{s} \theta CS_{s}' + \sum_{w} \theta' CW_{w}' + \sum_{m} \theta'' CM_{m}' + \sum_{d} \theta''' CD_{d}' \end{pmatrix} \end{pmatrix}$$
(20)

4.4. Constraints

 $\sum_{r \in R} SW^{o}_{swrt} \le 1 \qquad \forall s \in S, \forall w \in W, \forall t \in T, \forall o \in O$ (21)

$$\sum_{r \in R} WM^{o}_{wmrt} \le 1 \qquad \forall w \in W, \forall m \in M, \forall t \in T, \forall o \in O \qquad (22)$$

$$\sum_{r \in \mathbb{R}} MD^{o}_{mdrt} \leq 1 \qquad \forall m \in M, \forall d \in D, \forall t \in T, \forall o \in O \qquad (23)$$

$$\sum_{r \in R} DC_{dcrt}^{o} \le 1 \qquad \qquad \forall d \in D, \forall c \in C, \forall t \in T, \forall o \in O \qquad (24)$$

$$WM^{o}_{wmrt} \leq OW_{w} (1 - \eta^{o}_{wmrt}) \qquad \qquad \forall w \in W, \forall m \in M, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad \qquad \forall w \in W, \forall m \in M, \forall r \in R, \forall t \in T, \\ \forall w \in W, \forall m \in M, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad \qquad \forall w \in Q, \forall m \in M, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad \qquad \forall v \in Q, \forall m \in M, \forall r \in R, \forall t \in T, \end{cases}$$

$$(27)$$

$$\forall m \in M, \forall d \in D, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad \forall m \in M, \forall d \in D, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad \forall o \in O \qquad (29)$$

$$\sum_{(p,w,r)} TA^{o}_{ipswrt} \leq \left(1 - RT^{o}_{ist}\right) Cap^{Tr}_{ist} OS_{s} + ETC^{o}_{ist} \qquad \forall i \in I, \forall s \in S, \forall t \in T, \forall o \in O$$

$$(32)$$

$$\sum_{\substack{(p,m,r)}} TA_{ipwmrt}^{o} + \sum_{\substack{(p,\forall w' \in W/\{w\},r)}} TA_{ipww'rt}^{o} \qquad \forall i \in I, \forall w \in W, \forall t \in T, \forall o \in O \qquad (33)$$
$$\leq \left(1 - RT_{iwt}^{o}\right) Cap_{iwt}^{Tr} OW_w + ETC_{iwt}^{o}$$

$$\sum_{(d,r)} TA^{o}_{pmdrt} + \sum_{\left(\forall m' \in M / \{m\}, r\right)} TA^{o}_{pmm'rt} \\ \leq \left(1 - RT^{o}_{pmt}\right) Cap^{Tr}_{pmt} OM_{m} + ETC^{o}_{pmt}$$

$$\forall p \in P, \forall m \in M, \forall t \in T, \forall o \in O$$

$$(34)$$

$$\sum_{(c,r)} TA^{o}_{pdcrt} \leq \left(1 - RT^{o}_{pdt}\right) Cap^{Tr}_{pdt} OD_{d} + ETC^{o}_{pdt} \qquad \forall p \in P, \forall d \in D, \forall t \in T, \forall o \in O$$
(35)

$$\sum_{p \in P} IL_{ipwt}^{o} \le \left(1 - RH_{iwt}^{o}\right) Cap_{iwt}^{Ho} OW_{w} \qquad \forall i \in I, \forall w \in W, \forall t \in T, \forall o \in O$$
(36)

$$\sum_{p \in P} IL_{ipmt}^{o} \le \left(1 - RH_{imt}^{o}\right) Cap_{imt}^{Ho} OM_{m} \qquad \forall i \in I, \forall m \in M, \forall t \in T, \forall o \in O$$
(37)

$$PA_{pmt}^{o} \leq \left(1 - RP_{pmt}^{o}\right) Cap_{pmt}^{\Pr} OM_{m} \qquad \forall p \in P, \forall m \in M, \forall t \in T, \forall o \in O$$
(38)

$$\sum_{(m,r)} TA^{o}_{pmdrt} \leq (1 - RD^{o}_{pdt}) Cap^{De}_{pdt} OD_{d} \qquad \forall p \in P, \forall d \in D, \forall t \in T, \forall o \in O$$
(39)

$$\sum_{p \in P} TA^{o}_{pmdrt} \leq MD^{o}_{mdrt} BM \qquad \forall m \in M, \forall d \in D, \forall r \in R, \forall t \in T, \\ \forall o \in O \qquad (42)$$

$$\sum_{(d,r)} TA^{o}_{pmdrt} = PM^{o}_{pmt} \qquad \forall p \in P, \forall m \in M, \forall t \in T, \forall o \in O$$
(44)

$$\sum_{(m,r)} TA^{o}_{pmdrt} + \sum_{m \in M} PFE^{o}_{pmdt} = \sum_{(c,r)} TA^{o}_{pdcrt} \qquad \forall p \in P, \forall d \in D, \forall t \in T, \forall o \in O$$
(45)

$$\begin{aligned}
IL^{o}_{ipwt} &= IL^{o}_{ipwt-1} + \sum_{(s,r)} TA^{o}_{ipswrt} + \sum_{(w' \in W/\{w\},t)} TA^{o}_{ipw'wrt} & \forall i \in I, \forall p \in P, \forall w \in W, \forall t \in T, \\
&+ \sum_{s \in S} PFE^{o}_{ipswt} - \sum_{(m,r)} TA^{o}_{ipwmrt} - \sum_{(w' \in W/\{w\},t)} TA^{o}_{ipww'rt} & \forall o \in O
\end{aligned}$$
(46)

$$\begin{split} & L_{gyn}^{c} = L_{gyner}^{c} + \sum_{(x')} T_{gyner}^{A} + \sum_{(x')} T_{gyner}^{A} + \sum_{(w')} T$$

$\sum_{(i,p,w,r,t)} TA^{o}_{ipwmrt} + \sum_{(p,m'\in M/\{m\},r,t)} TA^{o}_{pm'mrt}$ $+ \sum_{(i,p,t)} \frac{PA^{o}_{pmt}}{\delta_{ip}} - \sum_{(p,m'\in M/\{m\},r,t)} TA^{o}_{pmm'rt}$ $\leq BM.CM_{m}' + \tau_{mo}^{NCr}$	$\forall m \in M, \forall o \in O$	(61)
$\sum_{(i,p,w,r,t)} TA^{o}_{ipwmrt} + \sum_{(p,m' \in M/\{m\},r,t)} TA^{o}_{pm'mrt}$ $+ \sum_{(i,p,t)} \frac{PA^{o}_{pmt}}{\delta_{ip}} - \sum_{(p,m' \in M/\{m\},r,t)} TA^{o}_{pmm'rt}$ $> \tau^{NCr}_{mo} CM_{m'}$	$\forall m \in M, \forall o \in O$	(62)
$\sum_{\substack{(p,m,r,t)\\(p,c,r,t)}} TA^{o}_{pmdrt} + \sum_{\substack{(p,m,t)\\pdcrt}} PFE^{o}_{pmdt}$ $+ \sum_{\substack{(p,c,r,t)\\pdcrt}} TA^{o}_{pdcrt} \leq BM.CD_{d}' + \tau^{NCr}_{do}$	$\forall d \in D, \forall o \in O \ \forall m \in M, \forall o \in O$	(63)
$\sum_{\substack{(p,m,r,t)\\ (p,c,r,t)}} TA^{o}_{pmdrt} + \sum_{\substack{(p,m,t)\\ pdcrt}} PFE^{o}_{pmdt}$ $+ \sum_{\substack{(p,c,r,t)\\ pdcrt}} TA^{o}_{pdcrt} > \tau^{NCr}_{do} CD_{d}'$	$\forall d \in D, \forall o \in O$	(64)
$TA^{o}_{ipswrt}, TA^{o}_{ipwmrt}, TA^{o}_{ipww'rt}, TA^{o}_{pmdrt}, TA^{o}_{pmm'rt}, TA^{o}_{pdcrt}, PM^{o}_{pmt}, IL^{o}_{ipmt}, IL^{o}_{ipwt}, LS^{o}_{pct} \ge 0$	$ \begin{aligned} \forall i \in I, \forall p \in P, \forall s \in S, \forall w \in W, \\ \forall m \in M, \forall d \in D, \forall c \in C, \forall o \in O, \\ \forall r \in R, \forall l \in L, \forall r \in R, \forall t \in T \end{aligned} $	(65)
$ETC_{ist}^{o}, ETC_{iwt}^{o}, ETC_{pmt}^{o}, ETC_{pdt}^{o}, PEI_{ipst}^{o},$ $PEI_{pmt}^{o}, PFE_{ipswt}^{o}, PFE_{pmdt}^{o} \ge 0$	$ \forall i \in I, \forall p \in P, \forall s \in S, \forall w \in W, \\ \forall m \in M, \forall d \in D, \forall c \in C, \forall l \in L, \\ \forall r \in R, \forall t \in T, \forall o \in O $	(66)
$OS_{s}, OW_{w}, OM_{m}, OD_{d}, SW_{swrt}^{o},$ $WM_{wmrt}^{o}, MD_{mdrt}^{o}, DC_{dcrt}^{o}, CS_{s}',$ $CW_{w}', CM_{m}', CD_{d}' \in \{0, 1\}$	$ \forall s \in S, \forall w \in W, \forall m \in M, \\ \forall d \in D, \forall c \in C, \forall l \in L, \\ \forall r \in R, \forall t \in T, \forall o \in O $	(67)

Constraints (21)-(24) enforce that only a single route can be determined between two different SC nodes in a given period. Constraints (25)-(31) ensure that if two facilities are allocated together via a particular route, facilities should exist or be established, and the route between them should not be disrupted. Constraints (32)-(35) stipulate that the amounts of transshipment from a particular node must not transgress the intended facility's transshipment capacity under partial disruption. Besides, some technical considerations for adjusting capacity – including opening candidate facilities, the possibility of manufacturing or supplying products, and considering the excess capacity planned because of proactive

resilience strategies – are taken into account. Constraints (36)-(37) provide that the amounts of inventory maintained by a node must not exceed the concerned facility's holding capacity under partial disruption. In addition, the situation of opening new facilities is considered. Constraint (38) ensures that the amounts of products manufactured at an MC must not transgress the intended facility's manufacturing capacity under partial disruption. Some technical considerations - including establishing candidate facilities, the possibility of manufacturing products, and considering the excess capacity planned because of preventive resilience strategies - are considered. Constraint (39) guarantees that the amounts of products distributed at a DC do not exceed the intended facility's distribution capacity under partial disruption, along with taking into account the excess capacity planned because of proactive resilience strategies. Constraints (40)-(43) enforce that as long as two facilities are not assigned together via a specified route, the flow of products cannot be transferred between them by that route. Constraints (44)-(45) are flow balance equations for MCs and DCs, respectively. Constraints (46)-(47) are inventory balance equations for depots and MCs. Constraint (48) provides demand satisfaction for product customer areas. Constraints (49)-(52) ensure that the amounts of excess transshipment capacity of a specified node must not transgress the amount of capacity lost due to disturbance risk along with taking into account technical considerations such as opening candidate facilities, the possibility of manufacturing or supplying of products, and the average recovery rate of the lost capacity at depots, MCs, and DCs. Constraints (53)-(54) ensure that the amounts of pre-positioned EI of products kept by fortified facilities cannot exceed the maximum holding capacities of pre-positioned EI of them. Constraints (55)-(56) provide that total purchased products from the pre-positioned EI of fortified facilities must not transgress the amount of pre-positioned EI kept by fortified facilities. Constraints (57)-(64) are employed to linearize non-linear equations (5)-(8) that represents the non-criticality of nodes RMSs, depots, MCs, and DCs, respectively. Constraints (65)-(67) represent positive and binary defined decision variables.

5. Solution Methodology

The deterministic model proposed in Section 4 is entangled with some issues as follows. First, due to the inherent uncertainties in parameters and fluctuations in the business environment, operational risks negatively impact the model. Consequently, a systematic procedure is required to cope with such threats. Second, the proposed formulation involves multiple OFs. Therefore, multi-objective programming (MOP) techniques should be employed to deal with this issue.

This study takes some measures to deal with the described concerns as follows:

- A two-stage stochastic formulation is applied to cope with operational risks.
- The ε-constraint method is employed to tackle the issue of multiple OFs in the proposed bi-objective stochastic model.

5.1. Applying MOP Techniques

MOP is an advantageous approach with proven achievements to solve multi-objective problems considering technical constraints that can deal with multiple OFs. This work applies the ε -constraint method to deal with multiple OFs. This method enables determining the Pareto frontier by obtaining efficient solutions and has illustrated success in the multi-objective SCND problem under operational and disruption risks (Olivares-Benitez et al., 2013). Besides, this method does not require the same units and scales for OFs.

Based on the ϵ -constraint method, the most desirable OF is taken into account as the primary OF, and the other OFs are transformed into constraints using ϵ bounds (Dehghani et

al., 2018). Upper and lower ε bounds are respectively determined for minimization and maximization OFs. The general formulation of the multi-objective model and solving methodology based on the described method is presented as follows.

Consider the following formulation for a problem with multiple OFs in the research area of SCND:

 $\begin{aligned} & \operatorname{Min} f_1, \dots, f_d, \dots, f_{j-1} \\ & \operatorname{Max} f_j, \dots, f_n \\ & St: \quad X \in \mathcal{Q} \end{aligned} \tag{68}$

The intersection of various constraints specifies Ω that indicates the feasible region. Note that f_d and ε represent the most desirable OF and the ε bound vector for the rest of OFs, respectively. The general formulation for transforming the multi-objective problem to an equivalent single-objective model is presented as follows.

$$\begin{array}{l} \text{Min } f_d \\ f_1 \leq \varepsilon_1 & , \dots, \ f_{d-1} \leq \varepsilon_{d-1} \\ f_{d+1} \leq \varepsilon_{d+1} & , \dots, \ f_{j-1} \leq \varepsilon_{j-1} \\ f_j \geq \varepsilon_j & , \dots, \ f_n \geq \varepsilon_n \\ X \in \Omega \end{array}$$

$$(69)$$

Notably, the Pareto optimal set can be attained by varying the epsilon bound vector along the Pareto frontier and optimizing generated equivalent single-objective problem in each iteration of the ε -constraint method.

6. Random Examples and Obtained Results

In this section, a numerical example with three random data sets is applied to evaluate the discussed formulation's performance and applicability, and the attained results are reported. The specifications of the random datasets are illustrated in Table 2. The model is coded and solved using the GAMS 25.2.4 and the CPLEX solver package. Besides, the code is executed in a computer with Intel Core i7 3610QM 2.3GHz and 8GB RAM DDR3 and Windows 10 operating system.

	<i>C</i>	D	<i>I</i>	M	P	Q	S	W	R	0	T
Dataset 1	4	5	7	4	5	5	5	4	3	5	5
Dataset 2	6	7	6	5	7	6	6	7	5	7	6
Dataset 3	8	8	9	7	9	8	7	8	7	9	8

Table 2. Specifications of Random Datasets

Note that some essential measures are required to validate and assess the proposed model's accuracy and applicability. In other words, it is necessary to implement sensitivity analysis to evaluate the influence of different parameters on OFs and the conflicts between OFs. This work also proposed a robust and resilient SCND considering uncertainty and risks of disturbance, so the advantages of robust and resilient design should be represented, respectively.

SCND entails both making strategic (pre-event) and operational (post-event) decisions, in which pre-event decisions include locating facilities and determining scenario independent variables. In contrast, post-event decisions clarify the executive mechanism. Table 3 illustrates the pre-event decisions of the concerned SC and the values of the attained values of OFs. The insights indicate that taking some measures, including opening fewer facilities and transshipment links and balancing the input and output flows to the opened facilities, lead to a

remarkable decline in the level of the TNRN, which will require extra charges and increases the TC of the system.

6.1. Numerical Results

6.1.1. The Conflict Between OFs and Plotting Pareto Frontier

Under the condition of conflict between OFs, the SCND problem can be modeled into a multi-objective formulation. According to Section 5-1, the solution optimal sets and Pareto frontiers can be achieved using the ε -constraint method by altering ε bounds in each iteration of the technique and optimizing the generated model. Note that strictly decreasing or increasing behavior in the Pareto frontier between two OFs indicates the conflict between them. In this study, OFs include minimizing the TCs of SC and the TNRN that the proposed analysis aims to assess conflicts between OFs and achieve Pareto frontier. Notably, TC is considered the primary OF, and ε indicates maximum TNRN in the ε -constraint method framework. Table 3 indicates the pre-event decisions of the concerned SC and the attained values of OFs. Figure 2 illustrates the conflict between TC and TNRN for three generated random datasets. The plotted Pareto frontier approximately behaves strictly decreasing for considered datasets, which means an increase in TC leads to a significant reduction in the TNRN. This behavior was predictable because any attempts to increase the network's resiliency and preparedness require expending extra costs. Besides, the Pareto frontiers' insights illustrate a particular trend, in which any increment in the amount of TC causes a relatively linear gradual decline. Note that the plots' line steepness does not represent considerable behavior and is different for all random datasets. Notably, the variations of SC size and the value for TNRN have a remarkable impact on SC costs.

		Dat	aset 1		
тс	TNIDN		Location	of SC nodes	
TC	TNRN	RMS	DE	MC	DC
757	496	2,4,5	1,3,4	1,2,4	1,3,5
818	432	2,4,5	1,4	1,3,4	1,3,4
933	285	1,3,4	2,3,5	1,2,4	2,3,5
1082	245	1,3,4	1,2,5	2,3,4	1,2,5
1233	167	2,4	3,5	1,3,4	1,4,5
1307	160	3,4	3,5	1,2,4	2,4,5
		Dat	aset 2		
тс	TNIDN		Location of	f SC nodes	
TC	TNRN -	RMS	DE	MC	DC
1200	680	1,3,5,6	1,3,5,7,8	1,2,3,5	2,4,5,7,8
1416	456	2,4,56	2,3,4,7,8	1,2,3,4	2,4,6,7,8
1529	347	1,2,5,6	1,3,5,7,8	2,3,4,5	1,3,6,7,8
1927	264	1,3,4,6	1,2,3,6,8	2,3,4,5	2,3,5,6,7
2389	180	2,3,5,6	2,4,5,7,8	1,3,4,5	1,3,4,5,7
3010	137	1,3,4	2,4,5	1,2,3,5	1,3,4,6
		Dat	aset 3		
тс	TNDN		Location of	SC nodes	
TC	TNRN -	RMS	DE	MC	DC
1664	973	1,2,7,8	1,3,5,6,7,8	2,4,5,7	1,3,4,7
1864	749	1,4,6,7	2,3,4,5,7,8	1,3,5,6,7	2,3,5,6
2255	644	1,2,4,6,7	1,3,5,6,7	2,3,4,6,7	2,4,5,6
2616	361	2,4,57	2,3,4,7,8	2,5,6,7	1,3,4,5
3505	282	1,3,5,6,7	2,4,7,8	2,3,4,7	1,3,4,5
4767	130	1,3,7,8	2,4,7,8	2,3,4,7	2,3,4,6

Table 3. Taken Pre-Event Decisions of the Concerned SC and the Attained Values of OFs

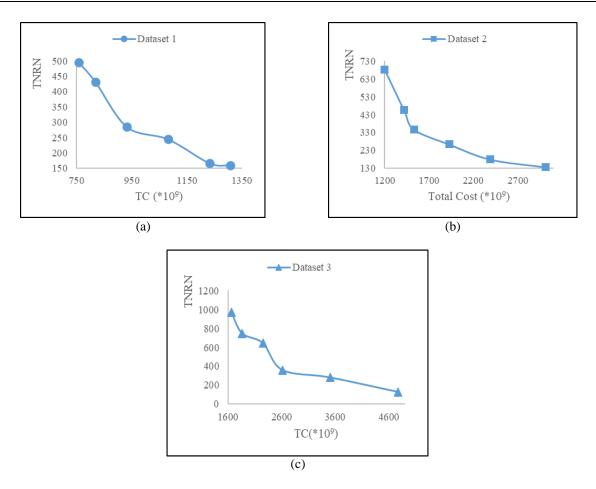


Fig. 2. The Conflict Between TC and TNRN

6.1.2. The Cost Performance of the Utilized Multiple Resilience Strategies

Resilience strategies are classified as preventive, and mitigation approaches. In this study, some structural resilience strategies, including multiple supplying (MS), maintaining prepositioned EI (MPEI), excess capacity (EC), lateral transshipment (LT), and network resiliency measures containing FC, NC, and NCr are taken into account simultaneously. This section addresses assessing the impact of implementing multiple strategies simultaneously on the proposed model's cost efficiency. To do so, we applied three random data sets to the proposed formulation to investigate the influences of multiple resilience strategies on the TC.

Figure 3 indicates the cost efficiency of employing multiple structural and network resiliency measures on the TC. The observed behavior illustrates that applying multiple structural strategies, including MS, MPEI, EC, and LT, will improve the cost-efficiency. Notably, adopting more structural strategies leads to a prominent and remarkable increment in cost efficiency. The logic behind this behavior is explained as follows. Taking more structural strategies satisfies customers' demands, decreases lost sales, and increases facilities' remaining capacity after a disruption. Thus, the TC of SC will reduce. The network resiliency and the reduction of the related criteria require high costs; since the network resiliency measures including NC, NCr, and FC are added to the structural resilience strategies containing MS, MPEI, EC, and LT, the cost efficiency gradually decreases.

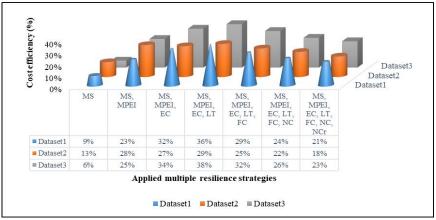


Fig. 3. The Cost Performance of Utilizing Multiple Structural and Network Resiliency Measures on the TC

6.1.3. Assessing the Impact of the Transshipment and Operational Capacity of Facilities

It is required to analyze the model's behavior in the situation of altering some specific parameters to ensure the validity of the proposed formulation. In other words, the impact of those parameters can be taken into consideration that is intensely influenced by external factors. To this aim, the transshipment and operational capacity of facilities are taken into account. Notably, operational capacity includes the manufacturing capacity of MCs, the holding capacity of DEs or MCs, and the delivery capacity of DCs. These measures are taken to examine the efficiency and applicability of facilities' capacity enhancement as a preventive resilience strategy.

Figure 4 illustrates the simultaneous impacts of altering the transshipment capacity of facilities on the TC and the TNRN of the SC. The observed pattern indicates that an increment in the transshipment capacity of facilities leads to a decline in the TC and an increase in the TNRN simultaneously and vice versa. Notably, similar behavior can be observed for all three random data sets. The logic behind this pattern can be described as follows. Increasing the transshipment capacity of facilities causes providing more products and enhancing the input and output flows to different nodes that lead to a remarkable decline in lost sales and the product inventories, which will decrease the shortage and holding costs so that the TC will be reduced. Besides, an increase in the number of opened facilities, the amount of flow between different nodes, and the number of active links will increase NCr, NC, and FC, leading to a significant increment in the TNRN.

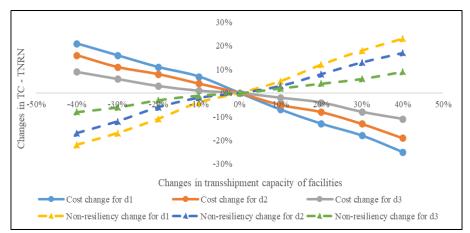


Fig. 4. Impact of Altering Transshipment Capacity of Facilities on the TC and the TNRN

6.2. Validation of the Stochastic Model

Ensuring the model validation is a significant issue in mathematical modeling that can be implemented based on both managerial and mathematical perspectives. Several methods, such as mathematical simulation, receiving expert opinions, comparing model results with historical data and information, and statistical analysis, can be employed to ensure the model's accuracy and validity. In this study, the TSSP is applied to the deterministic model to ensure the proposed stochastic model's applicability and validity. For this purpose, a numerical example containing three different random data sets is first applied to the investigated stochastic model. After the problem-solving process, the results are extracted.

Given that the proposed model is not applied to a case study, its validity cannot be examined from a managerial perspective. We only examine its validity from a mathematical point of view. Accordingly, a simulation approach is implemented to ensure the validation and real-world application of the proposed model. The steps of the mentioned method are as follows.

6.2.1. Simulation-Based Validation Approach

In this section, a simulation-based approach is employed to endorse model validation by comparing the performance of both deterministic expected value (EV) and stochastic models in terms of mean and standard deviation. It should be noted that uncertain parameters in the deterministic model are valued at their EV. Besides, the simulation process's performance is enhanced by determining binary variables in accordance with the main problem solutions for both deterministic EV and stochastic models. Accordingly, in each iteration of the simulation method, a new formulation is generated for both models, which are solved, and the associated results are extracted. It is worthy to note that the multi-objective model has converted into an equivalent single objective formulation via the ε constraint method.

Figure 5 demonstrates the implementation steps of the proposed model validation method. The steps of the validation approach employed in this research are as follows. Initially, parameters with the nature of uncertainty are generated employing uniform distributions based on deterministic data for each simulation iteration. Based on the previous step's uncertain parameters, both EV and stochastic models are generated and solved in each iteration. According to the obtained solutions, proportional infeasibility penalties are appended to all OFs (Dehghani et al., 2018). Ultimately, according to the discussed methodology, STC_{run} , and $STNRN_{run}$ representing the TC and TNRN of iteration run are valued, and both EV and stochastic models are evaluated and compared in terms of performance based on the average scores and standard deviations of the simulated OFs results.

Figure 6 illustrates the average score of the simulated OFs calculated for both EV and stochastic models under 120 simulation replications. Besides, it should be noted that the average scores of simulated OFs are compared with the results of solving the main problem. Based on observations, the average scores of simulated OFs are greater than the values of OFs in the main problem, which is a logical behavior. More precisely, in each simulation replication, several constraints become infeasible due to the generation of random uncertain parameters, which adds an infeasibility penalty to the OFs. It is important to note that the average score of the simulated OF is not a proper measure to consider EV and stochastic models' performance. Still, this measure is employed to calculate the standard deviations (SD) of simulated OFs, a reliable model validation indicator. Besides, TC, TNRN, STC, STNRN correspond to the optimal values of OFs in the main problem and the average score of simulated OFs, respectively.

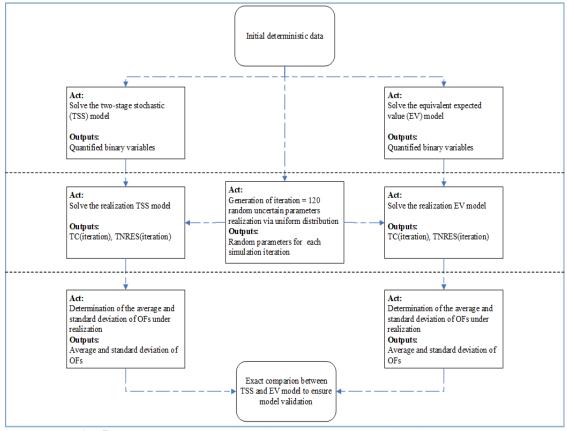


Fig. 5. The Implemented Simulation-Based Model Validation Approach

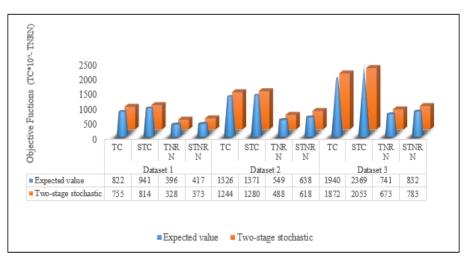


Fig. 6. Comparison Between the Primary and the Average Simulated OFs

According to previous discussions, the SD of simulated OF is an efficient measure to evaluate and validate the investigated stochastic model. It should be noted that the proposed model is valid only if the SDs of simulated OFs values calculated in the optimized stochastic formulation is less than the deterministic model.

Figure 7 illustrates that the calculated SD for the optimized simulated OFs in the stochastic model is lower than the deterministic formulation; therefore, the proposed stochastic model is mathematically valid and applicable.

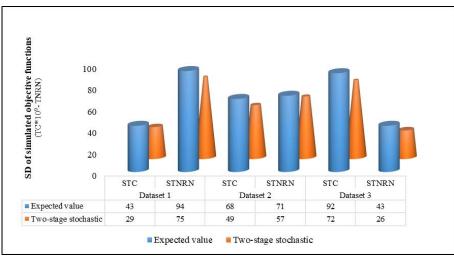


Fig. 7. Determining the Standard Deviation of All Simulated Objectives

7. Conclusion

Nowadays, the business environment is affected by varying unstable situations and fluctuations caused by different risks, including operational and human-made risks as well as natural disruptions. Thus, the lack of relevant managerial knowledge in this area can destructively affect SC's efficiency, performance, and productivity. Relevant studies in the area of RESCND have focused on identifying possible disruption scenarios, introducing preventive and mitigation structural resilience strategies, and employing various independent resilience strategies to cope with disturbance risks. Note that there is inadequate research on applying multiple strategies, considering complete disruptions in routes among facilities, utilizing network criteria including NC, NCr, and FC to reduce the level of network nonresiliency, and employing structural resilience strategies. This study presented a bi-objective multi-period model to design a resilient and stochastic five-echelon forward SC under operational risks and disruptions. The proposed model aims to minimize the total SC cost and the TNRN; notably, employing the ε -constraint method leads to coping with multiple OFs. Besides, we considered partial and multiple disruptions in all facilities and complete risks of disturbance in routes and links among SC nodes. Some preventive and mitigation measures are adopted simultaneously to fortify the structure and network of the SC against disruptions. Structural resilience strategies include multiple supplying, considering lateral transshipment, maintaining pre-positioned EI by fortified facilities and the possibility of purchasing from this type of stock, and determining excess capacity for facilities. In addition, the network nonresiliency consists of criteria including NC, NCr, and FC. Eventually, we managed operational risks by applying TSSP.

In this study, The SC consists of facilities including RMSs, DEs, MCs, and DCs. Strategic and operational decisions are made for the concerned SC under uncertainty and risks of disturbance. Decisions include locating facilities, determining the amount of transshipment between different network nodes, the level of emergency and standard inventory of facilities, and the amount of product lost sale in market zones. This study aims to achieve a network with a minimum TNRN and TC simultaneously. We applied three random datasets to the presented formulation to ensure the validity and applicability of the model. Ultimately, the numerical and managerial results of optimization are proposed.

Despite practical insights offered by the presented study, there are deficits in our work that researchers can take into consideration for further studies. Given that the concerned SC is dealing with various disruptions, applying some more preventive and mitigation measures

with proven successes can improve the system performance. Employing some resilience strategies such as reducing the density of the network, providing backup routes or facilities, and fortifying facilities are highly recommended to improve the preparedness and flexibility of the SC in the situation of disruption risks. Considering the public attention to SC's sustainability, researchers can evaluate SC activity or decision-making's social and environmental impacts. Besides, addressing the scheduling and routing decisions to minimize travel time in the proposed model can be an avenue for further research. Given the importance of increasing customer satisfaction, taking into account the shortage of products that have a nature of backlog and need to be provided efficiently and quickly leads to fulfilling this purpose. Our model's execution for large sizes requires applying proper solution algorithms such as cut and column, various types of benders decomposition, Lagrangian relaxation, and metaheuristic algorithms.

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