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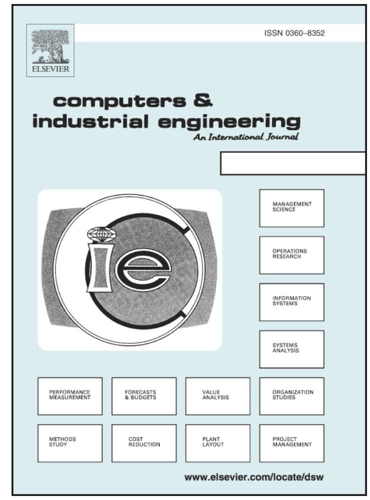

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Abstract. This paper introduces a multi-objective mathematical model to design a sustainable-resilient supply chain based on strategic and tactical decision levels. The resolution is to proactively plan for an optimal configuration to satisfy customer demands when the firm is highly vulnerable to operational and disruption risks. Compared to previous studies, we take the application of capacity planning in terms of redundancy to design a supply chain network that is resilient toward the demand-side by an optimization framework. A real-world influenza vaccine supply chain is studied to validate the proposed model and examine the tradeoff between resilience and sustainability. A robust fuzzy optimization approach is employed to cope with uncertainties. Then, the multi-objective model is solved by applying multi-choice goal programming with a utility function approach. Accordingly, managerial insights are suggested by analyzing the effects of structural parameters on the quantitative results. It is revealed that having redundancies in the supply chain does not always increase the total costs.

Keywords: Supply Chain Network Design; Sustainability; Resiliency; Robust Fuzzy Optimization; Multi-Choice Goal Programming with Utility Function.

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1. Introduction

Supply chains (SCs) are complex multi-level structures composed of diverse entities. SCs may exist, and function in the global or local form and have various configurations that range from simple forward flow production-distribution networks to closed-loop ones. These properties and improper designing and planning methodologies cause SCs to be vulnerable to operational or disruption risks (Tang, 2006), leading to adverse effects on their business-as-usual state (Christopher & Peck, 2004). The likelihood to face these risks has risen over recent years due to the lack of suitable forecast models and complex instincts of the SCs (Cardoso et al., 2015). Therefore, managers have stepped up analyses of these risks, both in terms of their impact and probability (Cunha et al., 2019). Recently, as governmental and societal communities have increased considerations of the triple bottom line (TBL) pillars announced in 1987 (Redclift, 2005), these concerns have intensified. Traditionally, SC's decision problems were settled only by regarding economic aspects. However, according to TBL, SCs should be more responsive to environmental and social measures legislated in several countries. In conclusion, a firm joined to or established in the SC, not only should be regarded with only a *resiliency* perspective but with *sustainability* measures further (Fahimnia & Jabbarzadeh, 2016; Zahiri et al., 2017).

The sustainability paradigm has been legislated for businesses to approach their goals without compromising the next generations to meet their needs (Bonevac, 2010). This is possible if SCs' adverse effects on the environment reduce. However, it should also be regarded by societal measures through the activity horizon of the SC (e.g., economic development, customer satisfaction), according to corporate social responsibility (CSR) (Dempsey et al., 2011). Concerns that exist in three decision-making levels of the SC (i.e., strategical, tactical, and operational) have increased in terms of all these three dimensions (i.e., economic, environmental, and social) (Ahi & Searcy, 2015). However, according to the conflicts these criteria may have, the SC's sustainable performance should not lower its resiliency (Fahimnia & Jabbarzadeh, 2016; Ivanov, 2018).

At first glance sustainability may result in increasing the total costs. However, it can lead to a drastic improvement in the profitability of the SC because sales may grow as customers' loyalty is intensified due to the logic that "how much sustainable their desired product is fabricated" (Whelan & Kronthal-Sacco, 2019). Concerning implementing the sustainability paradigm, there are several examples in real-world industries. For instance, Coca-cola reduced water usage by 20%, Adobe has reduced its greenhouse emissions by 75%, and Dell declined the energy intensity of its products by 20% (Confino, 2014). Moreover, in 2018 about 35% of supply chains tried to increase their responsibility due to the climate change (CDP, 2019, Bové & Swartz, 2016). Besides, in line with social goals, companies pursue wage negotiation, job creation, improving community services, product innovation, and improving their customer-centric attitudes (Eskandarpour et al., 2015). Subsequently, in today's competitive market, considering sustainability factors is critical to obtain competitive advantages and increase the profits of the SC.

Simultaneously, as a relatively novel concept included in decision-making, the resiliency paradigm forces firms to select a set of criteria to design the system's network and plan for fulfilling customers' requirements (Zhalechian et al., 2018). Accordingly, resiliency strategies aim to absorb adverse effects imposed by operational and disruption risks (Tang, 2006). This risk absorption procedure is done in such a way that the whole system (in our case, an SC) reaches its close-to-usual performance level (Craighead et al., 2007; Khalili et al., 2017; Sheffi & Rice, 2005). This aim is achievable by preparing for such risks proactively or projecting disaster scenarios for recovery in a reactive strategy (Zhalechian et al., 2018).

In the resiliency paradigm, the first step is to discuss a firm's vulnerability according to the probability of disruption and its consequences. Many firms prefer not to plan for disruptive events whenever there are low consequences or possibilities for natural (tsunami, fires, floods, etc.) or human-made (labors strike, suppliers unreliability, transportation failures, etc.) disaster scenarios (Hishamuddiin et al., 2015; Sheffi & Rice, 2005). It is because firms are more willing to develop those business continuity plans that can handle repetitive low-impact scenarios than sporadic high-impact ones (Chopra & Sodhi, 2004). Besides, planning for resilient systems ordinarily leads to higher total costs, which is not acceptable for top-level managers and stakeholders (Proag & Proag, 2014). At the same time, resiliency practices have several interactions with sustainability ones.

However, due to severe economic impacts that disruptions, especially recently, have led to, concerns are more profound than before. For instance, reports state that 74% of disruptions in the period between 1980 to 2012 were because of only extreme weather conditions, such as tsunami, volcano eruptions, etc. (The World Bank, 2013). Moreover, as a recent case, COVID-19 has forced firms to convert their "global" SC network to a "local one" by accelerating nearshoring and reshoring strategies (Barbieri et al., 2020). Overall, it is concluded that disruptions have become "the new (ab)normal" (Sheffi, 2020). Therefore, there are too many probable scenarios in which firms may suffer from a substantial economic failure due to today's widespread disruptive events.

Motivated by these concerns, there have been tries for developing integrated mathematical models in the recent decade. This trend corresponds to the industry 5.0 pillars, where sustainability and resilience are integrated for creating supply chains of the future (Breque et al., 2021). Current studies usually derive answers for the question, "To what extent does the SC's sustainability affect its resilience and contrariwise?". This answer is derived through a comprehensive study of the SC under each investigation and defining an integrated decision plan for identifying tradeoffs between traditional sustainable performance indicators with the new resilience level measure. Many researchers have adopted a disaster scenario analysis approach (Fahimnia & Jabbarzadeh, 2016; Mari et al., 2016). In such methods, the focus is more on the uncertainty of the design parameters in pre-/post-disruption phases but not the criteria for developing resilient SC configurations. Instead of this approach, tradeoffs between resiliency and sustainability objective functions (OFs) are derivable by multiple criteria/objective decision-making methods. Accordingly, a decision-maker would be able to design an SC such that its configuration, as a priority at the strategic level, is resilient. Note that regarding resilience measures, the quality of the network designed at the strategical level is most probable to influence the severity of the disastrous effects on the decisions in tactical (inventory, aggregate production) and operational (scheduling, routing) levels (Zhalechian et al., 2018).

Generally speaking, an alternative method to maintain resilience would be beneficial for firms that should be responsible in case of disasters. For instance, during the COVID-19 outbreak, the consumer demand in the health systems for masks, face shields, and ventilators intensified. This phenomenon continued so that manufacturers' existing capacity was not sufficient to respond to all of them. According to the SAP report by Gross (2020), an upcoming challenge for SCs would be on proposing distribution plans of the COVID-19 vaccine to the world. Existing methods in the literature only consider managerial-side resilience. Accordingly, the resilience is planned to increase the firm's viability and the SCs, neglecting the CSR in disastrous situations. Meanwhile, the others have proposed approaches that decrease unmet demand, either in a social or resilience objective, ignoring the redundant capacity requirements to materialize demand. This issue affects the required lead-time that matters for particular products (e.g., vaccines) to reach the market at the time of crisis. Thus, the simultaneous selection of such resilience measures, i.e., redundancy, lead-time, and customer de-service level, appears reasonable in SC's demand-side proactive resilience planning.

This paper proposes a novel mathematical model for an integrated strategic-tactical SC network design problem to measure resilience and sustainability's concurrent effects. Resiliency criteria such as capacity redundancy, lead time ratio, and customer de-service level are considered to proactively plan for possible disruptive events. Redundant capacity is an additional capacity that can replace the losses or shortages caused by a disruption (Sheffi & Rice, 2005). In this situation, the utilization rate of capacity redundancy increases, and the reactive contingency plans are activated. Moreover, we incorporate a relatively new concern, namely societal anxiety, to model CSR for firms, especially when consumers may be anxious about delivering their orders. Accordingly, we consider accessibility to the points of order fulfillment (here warehouses) as a tool to diminish the effect of these scenarios. The model relates societal anxiety to the surge of demand, a case where multiple firms experienced during the COVID-19 pandemic outbreak. The results help decision-makers reduce SC's vulnerability in mentioned scenarios and explore the new concept of redundancy and demand-side resilience in SC network design.

The rest of this paper is structured as follows. Section 2 reviews the related literature. After that, the problem under study is formulated mathematically in Section 3. Sections 4 and 5 are dedicated to applying the robust fuzzy method and the multi-choice goal programming solution approach. In Section 6, the suggested model is implemented to solve a real-world influenza vaccine SC problem in Iran. Also, a sensitivity analysis of some critical parameters is provided in this section for model validation. Accordingly, several managerial insights are recommended in Section 7. In the end, the overall conclusion of the study is presented in Section 8.

2. Literature review

In this section, we review studies that have developed and introduced integrated methods to evaluate the sustainability and resilience of the SCs simultaneously. Then, we end the discussion by analyzing the existing literature gap and claiming our contributions.

As an initial study, Carvalho et al. (2012) used total cost and lead time ratio as the SC performance measures for integrating sustainability and resiliency. The lead time ratio is calculated when the actual lead time is divided by the promised lead time. This criterion assesses each SC member's ability to comply with the lead time determined by their 1st-tier clients. The authors examined two approaches based on the creation of capacity redundancies and restructuring flexibilities to lessen adverse effects on SCs, in the case when a disruption occurs. Based on the results, they claimed that when the flexibility policy is employed, the SC's resulting costs are lower than the redundancy strategy that positively affects the lead time ratio. In the same year, Klibi and Martel (2012) took advantage of two other resiliency indicators, namely service level and multiple sourcing (also see works of Mousazadeh et al. (2015), Balaman and Selim (2016), and Dorneanu et al. (2019)). Their results show that multiple-sourcing models that allow several depots to serve customers are excellent for designing an effective and robust supply network.

Later Mari et al. (2014) presented an optimization model for designing a resilient-sustainable SC network in the clothing industry by incorporating carbon emission and flow maintenance indicators (also see Mari et al. (2016)). Maintaining a flow indicator defines the SC's ability to return to its original state or move to a more desirable state after being disturbed (Christopher & Peck, 2004). This indicator shows the SC's capability to plan for unexpected events, counteract disruptions, and survive them by holding operations continuity at the desired level of connectedness and control over structure and function (Ponomarov & Holcomb, 2009). Notably, Mari et al. (2014) claimed that reaching sustainability goals reduces deviations in resilience goals. Also, an economical SC has not only low sustainability but also is prone to disruption risks.

Cardoso et al. (2015) presented SC design and planning mathematical models containing implied demand uncertainty in five SC structures that encountered different types of disruptions, ranging from a simple forward chain to a complex closed-loop SC. This study applied several resiliency indicators, including service level, maintaining flows, node complexity (total number of nodes), node criticality (number of critical nodes), density (overall connectedness of a network, measured as the ratio between the number of actual ties and potential ties), and flow complexity (total number of flows). Moreover, the research aims to maximize the SC's economic sustainability by implementing the expected net present value of incomes and total costs. The findings maintain that having a resilient network structure from scratch necessitates fewer mitigation strategies to deal with disruptions. On the contrary, adding redundancy does not always return the most resilient SC (Sheffi, 2006). Disruption scenario and quality of service were introduced in the same year by Levalle and Nof (2015a) for evaluating the SC's resiliency (also see Torabi et al., (2015)).

Fahimnia and Jabbarzdeh (2016) came up with a mathematical model based on a scoring method for sustainability performance quantifying the SC's environmental and social impacts. Stochastic fuzzy goal programming was also employed to analyze sustainability tradeoff dynamically and design a "resiliently sustainable SC". In contrast with the other discussed studies, this study takes advantage of several sustainability indicators, including total costs, emissions, resource waste, product responsibility (i.e., customer privacy and product labeling), labor rights (i.e., forced labor, child labor, and discrimination incidents), and economic development (also see Pavlov et al. (2019)). According to their results, a sustainable SC developed based on analyzing the tradeoff cannot fulfill product demands statically when disruptions occur. However, a resiliently-sustainable SC designed by a dynamic analysis of sustainability tradeoff can satisfy all of the retailer demand with a little increase in total costs imposed by SC strategies and adjustments in disruptive events. Another new sustainability indicator, cap-and-trade, was introduced in the same year by Kaur and Singh (2019). Cap and trade or carbon emission trading is an approach that provides economic incentives to decrease the emissions of pollutants. It is also considered as a market-based government-mandated mechanism (also see Kaur et al. (2020), Jabbarzdeh et al. (2019), and Kogler and Rauch (2019)).

Jabbarzadeh et al. (2018) presented a hybrid method for a Sustainable-Resilient Supply Chain Network Design (SR-SCND) subjected to random disruptions, using redundancy and multiple sourcing resiliency indicators. They developed a stochastic bi-objective optimization model that quantifies and assesses how sustainable is the suppliers' performance by a fuzzy c-means clustering method. Their study concludes with out-sourcing decisions and resilience policies that minimize the expected total cost and maximize sustainable performance during disruptions. Zahiri et al. (2017) suggested a novel multi-objective integrated sustainable-resilient mixed-integer linear programming model for designing a pharmaceutical SC network under uncertainty. They developed a novel possibilistic-stochastic programming approach to cope with the uncertainty aspect of the model. The study's outcomes declare that manufacturers' and distribution centers' capacity levels play a crucial role in network resiliency. Ivanov (2018) analyzed disruption propagation in an SC while considering sustainability factors to design a resilient SC structure and following sustainability increase and ripple effect mitigation. Their simulation-based results play an undeniable role in identifying sustainability factors that mitigate the ripple effect in the SC and sustainability factors that enhance this effect. Recently, Gholami-Zanjani et al. (2021) tried to plan a food SC and concluded that resiliency strategies could efficiently recover the SC after experiencing disruptions while mitigating its environmental impacts. To convenience the readers, some relevant studies are compared and categorized in Table 1. As can be seen, studies are sporadically distributed in years between 2012 and 2021; however, they have been increased in frequency recently, which implies that academia and practitioners are more interested in designing and planning SCs according to both sustainability and resiliency practices.

2.1. Gap analysis and contributions

According to Table 1, few papers employed an integrated approach for strategic and tactical decision levels to design multi-product and multi-period SC networks. Besides, as far as we know, there is no optimization model using capacity redundancy, lead time ratio, and customer de-service level as proactive resiliency measures. Simultaneous consideration of these measures leads to improve responsiveness and resilience of the SC together. According to Cardoso et al. (2015), the lead time ratio measures the SC's response time after a disruption. This aids in alleviating challenges for the SC to face scenarios in which a surge of demand, mainly due to societal anxiety, occurs (in a crisis such as COVID-19) and to maintain optimal capacity for fulfilling customers.

Apart from this study's multi-dimensional view of these tailored resilience measures, the SC is planned based on demand-side resilience instead of managerial-side resilience. The effect of probable future scenarios is considered a whole, and the firm only desires to know how to plan the capacity to respond to future demand surges. Developing such strategies is beneficial to the firms when a disaster occurs and humanitarian logistics is activated to meet consumer demands. Therefore, capacity increases improve SC's resilience performance. Overall, we contend that demand-side resilience has been neglected among previous studies of the field or only considered as consumer de-service level. This novel kind of resilience planning accounts for both responsiveness and redundancy to decide optimal service levels in disastrous situations. A firm (such as a health system) is highly vulnerable to operational and disruption risks. Moreover, the model considers the sustainability objectives (i.e., economic, environmental, and social) for analyzing the interplays between them.

Briefly, this research proposes a novel variant of SR-SCND with the following specifications:

- A multi-objective robust fuzzy optimization model is employed to design a sustainable-resilient supply chain network under uncertainty integrating strategic and tactical decisions.
- Consideration of capacity redundancy, lead time ratio, and customer de-service level as resiliency measures simultaneously. Also, using proactive capacity planning to model the effects of redundancy on SC's resiliency.
- Consideration of decisions such as supplier selection and order allocation (SS&OA), continuous capacity planning, and delivery plans (contacts) for demand zones simultaneously. This integrated approach is beneficial to maintain SC's efficiency at its operational level.

- Consideration of deprivation factor, accessibility, and job creation as criteria for modeling CSR of the firms (to reduce lost sales, to reduce societal anxiety, and to increase economic development).
- A real case study (influenza vaccine SC in Iran) is investigated in this research. The results are also applicable for planning the COVID-19 vaccine distribution.

Table 1. Review of SR-SCND literature

Author(s) (Year)	Decision		Model		Outputs			Period	Transportation Mode	Technology level	Product	SC Performance Indicator																				Uncertainty Dealing Method	Solution Method	Case Study
												Sustainability										Resiliency												
												Economical		Environmental			Social					Service			Network									
																									Node					Flow				
	Strategic	Tactical	Simulation	Optimization	SS&OA	Capacity Planning	Delivery Contract					Total Costs	Net Present Value	Emissions	Resource waste	Cap and Trade	Product Responsibility	Labor rights	Job creation	Societal anxiety	Deprivation	Time	Level	Quality	Criticality	Complexity	Density	Redundancy	Failure	Complexity	Failure			
Carvalho et al. (2012)		✓	✓		✓			*M*			*S*	✓										✓										-	-	*A*
Klibi and Martel (2012)	✓	✓		✓				*M*			*S*	✓											✓						✓			-	*E*	-
Mari et al. (2014)	✓	✓		✓				*M*	✓		*S*	✓		✓																	✓	-	*E*	*C*
Cardoso et al. (2015)	✓	✓		✓		✓		*M*		✓	*M*	✓	✓										✓		✓	✓	✓			✓	✓	*S*	*E*	-
Levalle and Nof (2015a)		✓	✓		✓	✓		*S*			*S*	✓												✓					✓		✓	-	-	-
Levalle and Nof (2015b)		✓	✓		✓	✓		*S*			*S*	✓												✓							✓	-	-	-
Mousazadeh et al. (2015)	✓	✓		✓				*M*	✓	✓	*M*	✓											✓									*R*	*E*	*H*
Torabi et al. (2015)		✓		✓	✓			*S*			*M*	✓																	✓			*S*	*H*	-
Balaman and Selim (2016)	✓	✓		✓				*M*			*M*	✓											✓									*F*	*E*	*E*
Fahimnia and Jabbarzdeh (2016)	✓			✓	✓			*S*	✓		*M*	✓		✓	✓		✓	✓	✓										✓			*S*	*E*	*C*
Mari et al. (2016)	✓	✓		✓				*M*			*M*	✓		✓																	✓	*F*	*E*	*C*
Zahiri et al. (2017)	✓	✓		✓				*M*	✓	✓	*M*	✓				✓			✓				✓		✓	✓			✓			*F*	*H*	*P*
Ivanov (2018)		✓	✓		✓			*M*			*S*	✓		✓	✓								✓									-	-	-
Jabbarzadeh et al. (2018)	✓	✓		✓	✓	✓		*S*			*S*	✓		✓	✓		✓	✓	✓									✓	✓			*S*	*E*	*I*
Kaur and Singh (2019)		✓		✓	✓			*M*	✓		*M*	✓		✓		✓							✓									-	*E*	-
Dorneanu et al. (2019)	✓	✓		✓				*M*			*M*	✓											✓									-	*E*	*F*
Jabbarzadeh et al. (2019)	✓	✓		✓				*M*			*S*	✓		✓									✓									*R*	*E*	*E*
Kogler and Rauch (2019)		✓	✓					*M*			*S*	✓		✓								✓	✓									-	-	*W*
Pavlov et al. (2019)		✓		✓				*M*	✓	✓	*M*	✓		✓	✓														✓			*S*	*E*	*S*
Kaur et al. (2020)		✓		✓	✓			*M*			*M*	✓		✓		✓																*S*	*E*	-
Gholami-Zanjani et al. (2021)		✓		✓	✓		✓	*M*	✓		*M*	✓		✓																	✓	*S*	*E*	-
This Study	✓	✓		✓	✓	✓	✓	***M***	✓	✓	***M***	✓		✓					✓	✓	✓	✓	✓					✓				***R***	***E***	***P***

Note:
* For Period and Product, ***M*** Stands for "Multi", ***S*** for "Single".
* For Uncertainty Dealing Methods, ***S***: Stochastic, ***R***: Robust, ***F***: Fuzzy.
* For Solution methods, ***H*** Stands for "Heuristic, Metaheuristic", ***E*** for "Exact".
* For Case Studies, ***A***: Automotive, ***C***: Clothing, ***H***: Healthcare, ***E***: Energy, ***P***: Pharmaceutical, ***I***: Pipe industry, ***F***: Food industry, ***W***: Wood industry, ***S***: Seaports.

3. Decision framework

3.1. Problem statement

This paper aims to design an SC, including suppliers, manufacturing plants, warehouses, and customers, by minimizing imposed costs, minimizing negative social and environmental impacts on the chain while maximizing SC's resilience. The SC consists of some capacitated suppliers responsible for providing raw materials for a set of plants dispersed across the network. Deliverable items are to be shipped to warehouses before entering customer zones. The capacities of plants and warehouses are not pre-defined and are determined as an outcome of the proposed mathematical model. Different transportation modes with varying costs of traversing and pollution emissions are available to transport items between SC nodes. Fig. 1 demonstrates the described SC schematically.

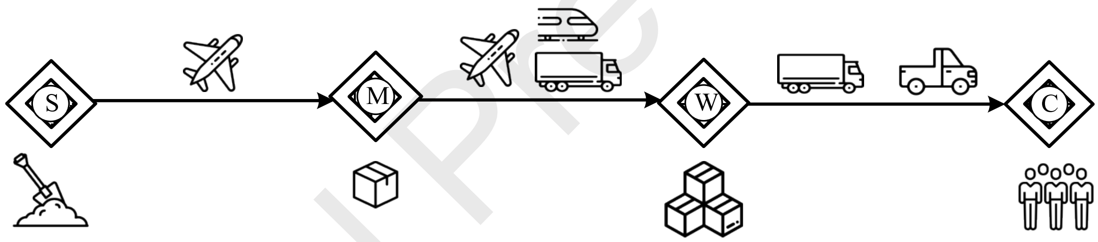


Fig. 1. The considered SC structure

The SC's environmental performance is controlled using the pollution emission factors per unit of distance related to different transportation modes. Three social factors, namely deprivation, accessibility, and job creation factors, are employed to take the SC's social performance into account. The deprivation factor quantifies the SC's tarnished reputation when it fails in satisfying a customer zone's demand (i.e., lost sales). The accessibility factor measures the possibility of serving consumer demand from multiple warehouses, which leads to increased quality of life by a decrease in societal anxiety about the impossibility of order deliveries at the time of disastrous events. Finally, the job creation factor calculates the effects of having a specific employment rate based on manufacturing plants' technology level.

For having a proactively resilient SC towards disruptions, three performance measures, including lead time ratio, flexibly capacitated plants, and warehouses in terms of redundancy and customer de-service level effects, are applied. Notably, except for redundancy, others are modified versions of standard resilience measures in the literature (Carvalho et al., 2012; Zahiri et al., 2017). All these performance measures have penalties/rewards defined by resiliency factors which are to be determined by the decision-maker. According to how much the decision-makers are concerned about the criticality of the resiliency measures, i.e., a unit of increase in the lead time, redundancy in the SC of capacity, or improvement of the demand-side resilience, the resiliency factors can have higher or lower values.

The goal of the mathematical model presented in this section is to ascertain sourcing strategies for multiple periods over the planning horizon (i.e., selection of the supplier and the order quantity) besides network design decisions (i.e., the capacity and location of plants and warehouses) so that not only total costs of the SC is minimized, but also its resiliently sustainable performance is maximized. This is applicable through proactive strategy in both typical and disastrous situations. The process flow of this research is illustrated in Fig. 2.

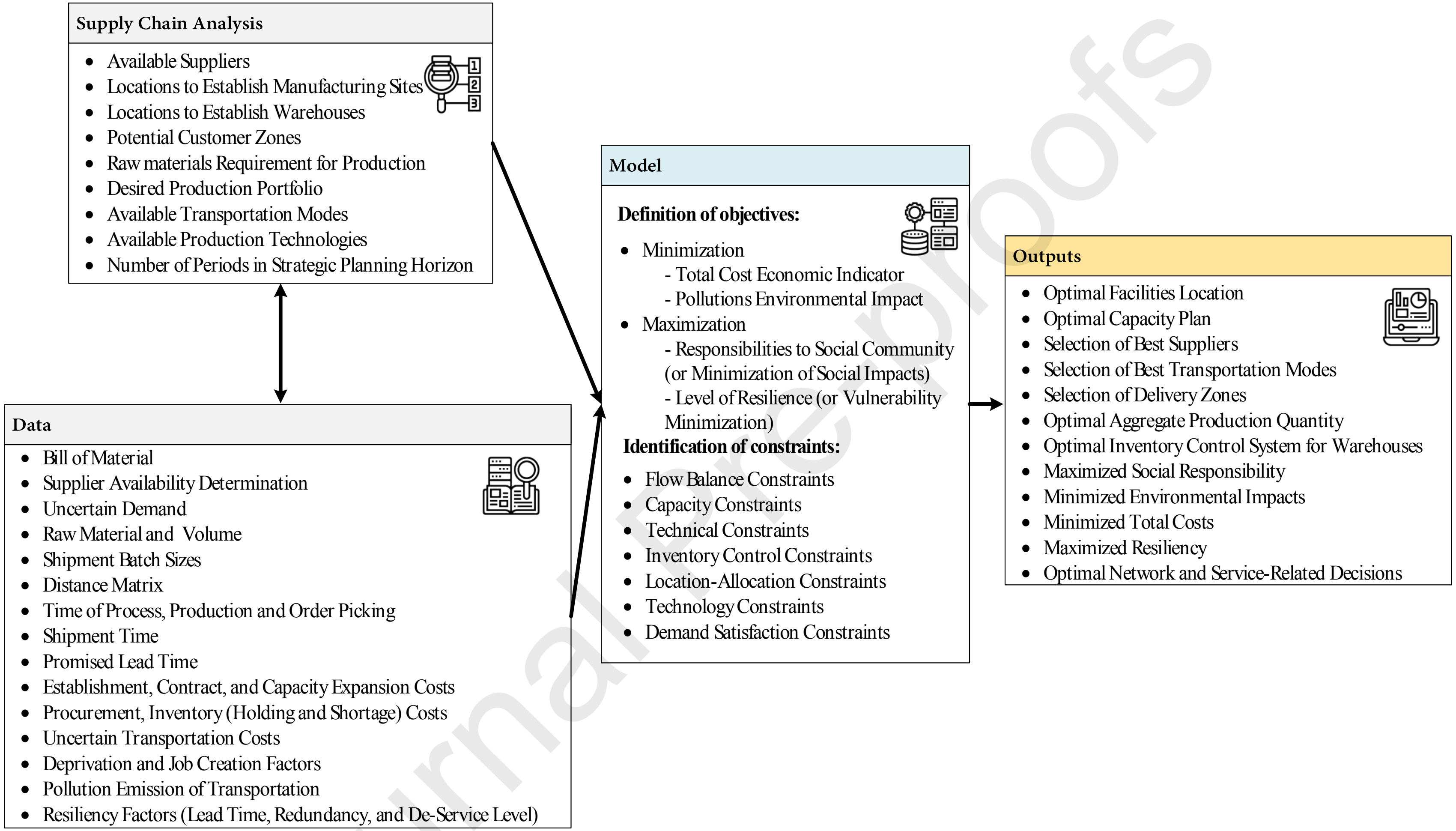


Fig. 2. A conceptual outline of the research process

3.2. A multi-objective mathematical model

The general form for the multi-objective optimization model is as follows.

Model 1: Deterministic SR-SCND

OF 1: $Min\ Z_1 = Economic\ Indicator$

OF 2: $Min\ Z_2 = Environmental\ Impacts$

OF 3: $Max\ Z_3 = Social\ Responsibility$

OF 4: $Max\ Z_4 = Resilience\ Level$

s.t.

Constraints

In the sequel, each part of this mathematical model is described in detail.

3.2.1. Notations:

The notations below are introduced and categorized to formulate the problem under study mathematically.

Sets

SC Entities

$\mathbb{S}$	Set of suppliers, $s \in S$
$\mathbb{M}$	Set of candidate manufacturing plants, $m \in M$
$\mathbb{W}$	Set of candidate warehouses, $w \in W$
$\mathbb{C}$	Set of customer zones, $c \in C$

Others

$\mathbb{R}$	Set of raw materials, $r \in R$
$\mathbb{I}$	Set of deliverable items, $i \in I$
$\mathbb{L}$	Set of technology levels, $l \in L$
$\mathbb{A}$	Set of available transportation modes for shipping items from plants to warehouses, $a \in A$

$\mathbb{B}$	Set of available transportation modes for shipping items from warehouses to customer zones, $b \in B$
$\mathbb{T}$	Set of periods in the strategic planning horizon, $t \in T$

Technical Parameters

Logical

α_{ri}	Percentage of raw material $r \in R$ required for producing a unit of item $i \in I$
δ_{rsm}	Availability of supplier $s \in S$ to provide raw material $r \in R$ for plant $m \in M$
M	Big-M value

Capacity/Volume - Unit: Liters (L)

$\tilde{d}_{ict}$	Demand for item $i \in I$ from customer zone $c \in C$ in period $t \in T$
θ_i	Volume of one package of item $i \in I$
θ'_r	Volume of one package of raw material $r \in R$
q^S_{rs}	Batch size for shipping raw material $r \in R$ from supplier $s \in S$
q^M_{ia}	Batch size for shipping item $i \in I$ with transportation mode $a \in A$ from plants
q^W_{ib}	Batch size for shipping item $i \in I$ with transportation mode $b \in B$ from warehouses
k_{rs}	Overall capacity of supplier $s \in S$ for raw material $r \in R$
K^{Min}_{mt}	Minimum time-based capacity of plant $m \in M$ in period $t \in T$
K^{Max}_{mt}	Maximum time-based capacity of plant $m \in M$ in period $t \in T$
K'^{Min}_{w}	Minimum volume-based capacity of warehouse $w \in W$ for all periods
K'^{Max}_{w}	Maximum volume-based capacity of warehouse $w \in W$ for all periods
I^{init}_{iw}	Initial inventory of item $i \in I$ at warehouse $w \in W$

Distance - Unit: Kilometers (km)

κ^{SM}_{sm}	Distance between supplier $s \in S$ and plant $m \in M$
κ^{MW}_{mw}	Distance between plant $m \in M$ and warehouse $w \in W$
κ^{WC}_{wc}	Distance between warehouse $w \in W$ and customer zone $c \in C$

Time – Unit: Days

$\tilde{\vartheta}^{S}_{rs}$	Processing time for raw material $r \in R$ provided by supplier $s \in S$
ϑ^{M}_{ilm}	Manufacturing time to produce a unit of item $i \in I$ with technology level $l \in L$ in plant $m \in M$
$\tilde{\vartheta}^{W}_{iw}$	Order picking time to collect a unit of item $i \in I$ in warehouse $w \in W$
$\tilde{\xi}^{SM}_{sm}$	Average shipment time between supplier $s \in S$ and plant $m \in M$
$\tilde{\xi}^{MW}_{mw}$	Average shipment time between plant $m \in M$ and warehouse $w \in W$
$\tilde{\xi}^{WC}_{wc}$	Average shipment time between warehouse $w \in W$ and customer zone $c \in C$
L^{S}_{rst}	Promised lead time by supplier $s \in S$ for procurement of raw material $r \in R$ in period $t \in T$
L^{M}_{imt}	Promised lead time by plant $m \in M$ for the replenishment of item $i \in I$ in period $t \in T$
L^{W}_{iwt}	Promised lead time by warehouse $w \in W$ for shipment of item $i \in I$ to customer zones in period $t \in T$

Economical Parameters

Strategic Costs - Unit: Dollars ($)

f^{M}_{ml}	Establishment cost of plant $m \in M$ with technology level $l \in L$
f^{W}_{w}	Establishment cost of warehouse $w \in W$
υ^{S}_{st}	Cost of the supply contract with supplier $s \in S$ in period $t \in T$
υ^{WC}_{wc}	Cost of the delivery contract between warehouse $w \in W$ and customer zone $c \in C$
ϕ^{V}_{w}	Cost of acquiring capacity per volume unit for warehouse $w \in W$
ϕ^{T}_{m}	Cost of acquiring capacity per time unit for plant $m \in M$
p^{S}_{rs}	Cost of procuring a unit of raw material $r \in R$ by supplier $s \in S$
p^{M}_{im}	Cost of producing a unit of item $i \in I$ by plant $m \in M$

Tactical Costs - Unit: Dollars ($)

$\tilde{\tau}^{S}_{s}$	Traversing cost per unit of distance by supplier $s \in S$
$\tilde{\tau}^{A}_{a}$	Traversing cost per unit of distance by mode $a \in A$

$\tilde{\tau}_b^B$	Traversing cost per unit of distance by mode $b \in B$
h_i	Holding cost for a unit of item $i \in I$
π_i	Shortage cost for a unit of item $i \in I$
Social Parameters	
ϱ_{ic}	Deprivation factor for a unit of unsatisfied demand from customer zone $c \in C$related to item $i \in I$
ϖ_{1ml}	Job creation factor for establishing plant $m \in M$ with technology $l \in L$
ϖ_{2wc}	Accessibility factor obtained for assigning warehouse $w \in W$ (order fulfillment point) to customer zone $c \in C$
Environmental Parameters	
Transportation pollutions – Unit: kgCO2	
$\tilde{\rho}_s^S$	Pollution emitted per unit of distance by supplier $s \in S$
$\tilde{\rho}_a^A$	Pollution emitted per unit of distance by transportation mode $a \in A$
$\tilde{\rho}_b^B$	Pollution emitted per unit of distance by transportation mode $b \in B$
Resiliency Parameters	
$\tilde{\mathfrak{R}}^T$	Resiliency factor per unit of increase in lead time
$\tilde{\mathfrak{R}}_m^M$	Resiliency factor per unit of increase in capacity in plant $m \in M$
$\tilde{\mathfrak{R}}_w^W$	Resiliency factor per unit of increase in capacity in warehouse $w \in W$
$\tilde{\mathfrak{R}}_c^D$	Resiliency factor per unit of unmet demand in customer zone $c \in C$
Decision variables	
Binary	
X_{st}^S	=1 if supplier $s \in S$ is selected in period $t \in T$, otherwise =0
X_{ml}^M	=1 if plant $m \in M$ is established with technology level $l \in L$, otherwise =0
X_w^W	=1 if warehouse $w \in W$ is established, otherwise =0
X_{wc}^{WC}	=1 if customer zone $c \in C$ is assigned to warehouse $w \in W$, otherwise =0

Continuous

Q^{SM}_{rsmt}	Quantity of raw material $r \in R$ shipped from supplier $s \in S$ to plant $m \in M$ in period $t \in T$
P_{imt}	Quantity of item $i \in I$ produced by plant $m \in M$ in period $t \in T$
Y^{MW}_{imwat}	Quantity of item $i \in I$ shipped from plant $m \in M$ to warehouse $w \in W$ in period $t \in T$ using transportation mode $a \in A$
Y^{WC}_{iwcbt}	Quantity of item $i \in I$ shipped from warehouse $w \in W$to customer zone $c \in C$ in period $t \in T$using transportation mode $b \in B$
K^{M}_{mt}	Time-based capacity of plant $m \in M$ in period $t \in T$
K^{W}_{w}	Volume-based capacity of warehouse $w \in W$
L^{C}_{ict}	Quantity of unsatisfied demands from customer zone $c \in C$related to item $i \in I$ in period $t \in T$
I^{W}_{iwt}	Quantity of item $i \in I$at warehouse $w \in W$ in period $t \in T$

3.2.2. Assumptions

The critical assumptions of the whole SC system that is going to be analyzed are summarized as below:

1. The SC consists of three echelons (i.e., suppliers, plants, and warehouses).
2. The flow between suppliers and plants is in the form of raw material, and the flow starting from plants and ending to customer zones is in the form of the final product (i.e., single level manufacturing system is deployed).
3. No shipment is possible from plants to customer zones.
4. Only one warehouse should be allocated to each customer zone (i.e., single assignment).
5. The actual lead time for entity j in the SC is calculated as follows (Carvalho et al., 2012):

$$LT_{Actual_j} = \left(\vartheta_j + \frac{\xi_{j(j+1)}}{\theta q_j}\right) F_{j(j+1)}$$

Where ϑ_j signifies the processing time of a unit of raw material/product in the entity, q_j represents the batch size of shipments, and θ is the volume of one package of raw material/product. Respectively, $\xi_{j(j+1)}$ and $F_{j(j+1)}$ denote the average shipment time and the overall raw material/product flow between two subsequent entities. To calculate the "lead time ratio", the actual lead time needs to be divided by the promised lead time as follows:

$$LTR_j = \frac{LT_{Actual_j}}{LT_{Promised_j}}$$

For further analysis, refer to Fig. 3. In an ideal SC, all entities' lead time ratios take on values between 0 and 1 (see case 2). As it is seen, any undesired event at the upstream (here at the supply side) causes the end customers to experience an inevitable delay in receiving the orders due to the domino effect (case 3). These adverse effects are more intense compared to case 2. However, it is possible to improve the SC performance by devising well-designed proactive plans that focus on keeping the lead time ratio in the (0,1] interval.

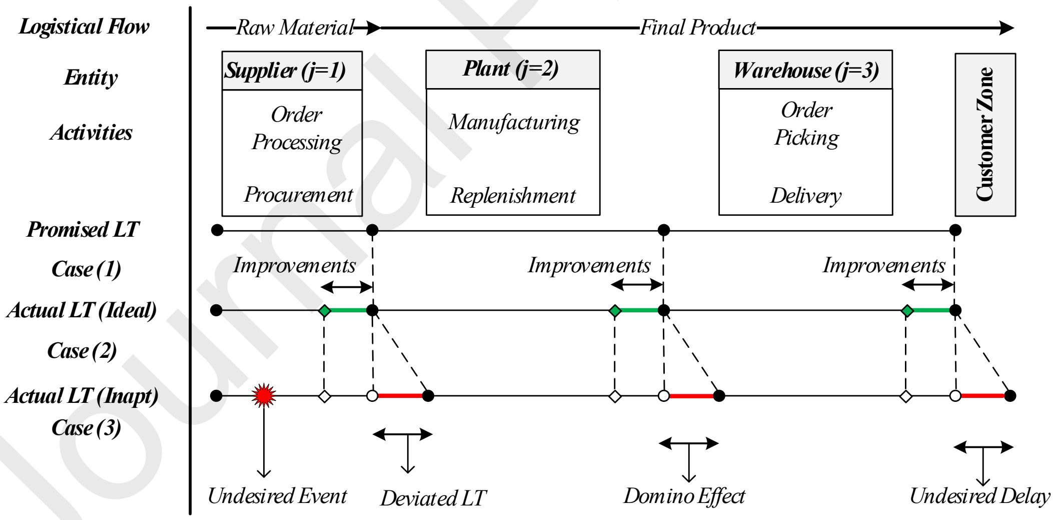


Fig. 3. Schematic view of service lead time in the SC and at a single period.

6. Acquiring capacity for facilities increases costs but also increases resiliency.
7. Capacity is planned rather than discrete pre-considered values that are in terms of capacity levels.
8. Transportation flows emit CO2-based pollutions.
9. Unsatisfied demands are lost, i.e., no backordering is allowed.
10. SC acts in seasonal time slots.

The first OF (OF1) consists of two types of costs: Tactical and strategic costs, each of which can be categorized into smaller sub-groups. Strategic costs esteem from strategic SC decisions and are before the tactical ones. These costs include establishment (plants and warehouses), accruing capacity, and supply and delivery contract costs. In contrast, tactical costs comprise those from procurement, production, inventory (holding plus shortage), and transportation (between SC entities). The mathematical representation of the economic indicator is as follows:

$$\begin{aligned}\boldsymbol{Min}\, Z_1 = &\underbrace{\sum_{m\in M}\sum_{l\in L} f_{ml}^{M} X_{ml}^{M} + \sum_{w\in W} f_{w}^{W} X_{w}^{W}}_{Establishment} + \underbrace{\sum_{m\in M}\sum_{t\in T}\phi_{m}^{T} K_{mt}^{M} + \sum_{w\in W}\phi_{w}^{V} K_{w}^{W}}_{Capacity\ Acquiring} + \underbrace{\sum_{s\in S}\sum_{t\in T} \upsilon_{st}^{S} X_{st}^{S} + \sum_{w\in W}\sum_{c\in C}\upsilon_{wc}^{WC} X_{wc}^{WC}}_{Supply\ and\ delivery\ Contracts}\\ &+ \underbrace{\sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T} p_{rs}^{S} Q_{rsmt}^{SM}}_{Procurement} + \underbrace{\sum_{i\in I}\sum_{m\in M}\sum_{t\in T} p_{im}^{M} P_{imt}}_{Production} + \underbrace{\sum_{i\in I}\sum_{w\in W}\sum_{t\in T} h_i I_{iwt}^{W} + \sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\pi_i L_{ict}^{C}}_{Inventory}\\ &+ \underbrace{\sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T}\tilde{\tau}_{s}^{S}\frac{\kappa_{sm}^{SM}}{\theta'_{r} q_{rs}^{S}} Q_{rsmt}^{SM} + \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A}\sum_{t\in T}\tilde{\tau}_{a}^{A}\frac{\kappa_{mw}^{MW}}{\theta_i q_{ia}^{M}} Y_{imwat}^{MW} + \sum_{i\in I}\sum_{w\in W}\sum_{c\in C}\sum_{b\in B}\sum_{t\in T}\tilde{\tau}_{b}^{B}\frac{\kappa_{wc}^{WC}}{\theta_i q_{ib}^{W}} Y_{iwcbt}^{WC}}_{Transportation}\end{aligned} \quad \text{(OF1)}$$

The second OF (OF2) calculates the total pollution emissions resulting from all traverses in the SC. This objective should be minimized to design an environmentally-sustainable (Green) SC.

$$\begin{aligned}\boldsymbol{Min}\, Z_2 &\\ = &\sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T}\tilde{\rho}_{s}^{S}\frac{\kappa_{sm}^{SM}}{\theta'_{r} q_{rs}^{S}} Q_{rsmt}^{SM}\\ &+ \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A}\sum_{t\in T}\tilde{\rho}_{a}^{A}\frac{\kappa_{mw}^{MW}}{\theta_i q_{ia}^{M}} Y_{imwat}^{MW} + \sum_{i\in I}\sum_{w\in W}\sum_{c\in C}\sum_{b\in B}\sum_{t\in T}\tilde{\rho}_{b}^{B}\frac{\kappa_{wc}^{WC}}{\theta_i q_{ib}^{W}} Y_{iwcbt}^{WC}\end{aligned} \quad \text{(OF2)}$$

The third OF (OF3) minimizes deviations from ideal social responsibility indicators, where the weights ω_1 and ω_2 control the relative importance of the considered social objectives. Accordingly, the job creation and accessibility criteria increase (to improve social welfare), and the amount of lost sales decrease (to decrease deprivation).

$$\begin{aligned}\boldsymbol{Min}\, Z_3 &\\ = \omega_1 &\left(\frac{\left[\sum_{m\in M}\sum_{l\in L}\varpi_{1ml}X_{ml}^{M} + \sum_{m\in M}\sum_{l\in L}\varpi_{2wc}X_{wc}^{WC}\right]^{max} - \left[\sum_{m\in M}\sum_{l\in L}\varpi_{1ml}X_{ml}^{M} + \sum_{m\in M}\sum_{l\in L}\varpi_{2wc}X_{wc}^{WC}\right]}{\left[\sum_{m\in M}\sum_{l\in L}\varpi_{1ml}X_{ml}^{M} + \sum_{m\in M}\sum_{l\in L}\varpi_{2wc}X_{wc}^{WC}\right]^{max} - \left[\sum_{m\in M}\sum_{l\in L}\varpi_{1ml}X_{ml}^{M} + \sum_{m\in M}\sum_{l\in L}\varpi_{2wc}X_{wc}^{WC}\right]^{mi}}\right.\\ &\left(\frac{\sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\varrho_{ic}L_{ict}^{C} - \left[\sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\varrho_{ic}L_{ict}^{C}\right]^{min}}{\left[\sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\varrho_{ic}L_{ict}^{C}\right]^{max} - \left[\sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\varrho_{ic}L_{ict}^{C}\right]^{min}}\right)\end{aligned} \quad \text{(OF3)}$$

According to Zahiri et al .(2017), max and min values in (OF3) are parameters, which are calculated in two sub-optimization problems under maximization (to get the max value) and minimization (to get the min value). Finally, proactive resiliency is considered, in terms of the network (capacity redundancy) and service (lead time ratio and service level), as shown in the fourth OF (OF4).

$$\boldsymbol{Max}\ Z_4$$

$$= \underbrace{\sum_{m \in M}\sum_{t \in T}\tilde{\mathfrak{R}}^M_m K^M_{mt} + \sum_{w \in W}\tilde{\mathfrak{R}}^W_w K^W_w}_{Redundancy} - \tilde{\mathfrak{R}}^T \Bigg[\underbrace{\sum_{r \in R}\sum_{s \in S}\sum_{m \in M}\sum_{t \in T}\frac{\left(\tilde{\vartheta}^S_{rs} + \frac{\tilde{\xi}^{SM}_{sm}}{\theta'_r q^S_{rs}}\right)Q^{SM}_{rsmt}}{L^S_{rst}}}_{Supplier\ LTR}$$

$$+ \underbrace{\sum_{i \in I}\sum_{l \in L}\sum_{m \in M}\sum_{w \in W}\sum_{a \in A}\sum_{t \in T}\frac{\left(\vartheta^M_{ilm} + \frac{\tilde{\xi}^{MW}_{mw}}{\theta_i q^M_{ia}}\right)P_{imt}}{L^M_{imt}}}_{Manufacturer\ LTR} + \underbrace{\sum_{i \in I}\sum_{w \in W}\sum_{c \in C}\sum_{b \in B}\sum_{t \in T}\frac{\Big(\tilde{\vartheta}^W_{iw}}{}}_{Warehouse\ LT} \qquad \text{(OF4)}$$

$$\Bigg] - \underbrace{\sum_{i \in I}\sum_{c \in C}\sum_{t \in T}\tilde{\mathfrak{R}}^D_c L^C_{ict}}_{De-Service\ Level}$$

3.2.4. Constraints:

Achieving optimality for the OFs mentioned above requires meeting several logical constraints as follows:

$$L^C_{ict} + \sum_w\sum_b Y^{WC}_{iwcbt} \geq \tilde{d}_{ict} \qquad \forall i \in I, \forall c \in C, \forall t \in T \qquad (1)$$

$$\sum_i\sum_b Y^{WC}_{iwcbt} \leq X^{WC}_{wc}M \qquad \forall w \in W, \forall c \in C, \forall t \in T \qquad (2)$$

$$X^{WC}_{wc} \leq X^W_w \qquad \forall w \in W, \forall c \in C \qquad (3)$$

$$\sum_w X^{WC}_{wc} \leq 1 \qquad \forall c \in C \qquad (4)$$

$$I^W_{iwt} + \sum_c\sum_b Y^{WC}_{iwcbt} = I^W_{iw(t-1)} + \sum_m\sum_a Y^{MW}_{imwat} \qquad \forall i \in I, \forall w \in W, \forall t \in T/\{0\} \qquad (5)$$

$$I^W_{iwt} = I^{init}_{iw} \qquad \forall i \in I, \forall w \in W, \forall t \in \{0\} \qquad (6)$$

$$\sum_w\sum_a Y^{MW}_{imwat} = P_{imt} \qquad \forall i \in I, \forall m \in M, \forall t \in T \qquad (7)$$

$$\sum_i\sum_t I^W_{iwt} + \sum_i\sum_c\sum_b\sum_t Y^{WC}_{iwcbt} \leq K^W_w \qquad \forall w \in W \qquad (8)$$

$$K^W_w \leq X^W_w M \qquad \forall w \in W \qquad (9)$$

$$P_{imt} \leq X^M_{ml}M \qquad \forall i \in I, \forall l \in L, \forall m \in M, \forall t \in T \qquad (10)$$

$$\sum_l X^M_{ml} \leq 1 \qquad \forall m \in M \qquad (11)$$

$$\sum_i\sum_l \vartheta^M_{ilm}P_{imt} \leq K^M_{mt} \qquad \forall m \in M, \forall t \in T \qquad (12)$$

$P_{imt} \leq \sum_{r \in R} \alpha_{ri} Q^{SM}_{rsmt}$	$\forall i \in I, \forall m \in M, \forall s \in S, \forall t \in T$	(13)
$Q^{SM}_{rsmt} \leq \delta_{rsm} k_{rs} X^{S}_{st}$	$\forall r \in R, \forall s \in S, \forall m \in M, \forall t \in T$	(14)
$K^{Min}_{mt} \leq K^{M}_{mt} \leq K^{Max}_{mt}$	$\forall m \in M, \forall t \in T$	(15)
$K'^{Min}_{w} \leq K^{W}_{w} \leq K'^{Max}_{w}$	$\forall w \in W$	(16)
$X \in \{0,1\}$	For all establishments, assignments, and supplier selection decisions	(17)
$Y \geq 0$	For all flows	(18)
$Q \geq 0$	For order quantity	(19)
$P \geq 0$	For production quantity	(20)
$K \geq 0$	For capacity	(21)
$I \geq 0$	For held inventory	(22)
$L \geq 0$	For lost sales	(23)

Constraint (1) ensures that the customer zone's demand should be either met or, if unsatisfied, should be lost for each item and all periods. According to Constraints (2) and (3), there can be no flow between a particular warehouse and a customer zone unless the customer zone is established and assigned to the warehouse in advance. Constraint (4) allows assigning a customer zone to only one warehouse. Constraints (5)-(7) ensure the flow balance between plants and warehouses, considering a desired initial inventory for warehouses at the beginning of the planning horizon. Constraint (8) enforces the warehouse's capacity to be larger than held stock plus delivered items to customer zones. Constraint (9) allows capacity acquiring for a warehouse, if and only if it is established in advance. Constraint (10) applies the same, but for production volume in plants. Based on Constraint (11), only one technology level can be considered for each manufacturing plant. Constraints (12) and (13) enforce considerations related to production limitations due to production capacity and the number of raw materials provided by suppliers, respectively. Finally, the fulfillment of raw materials required by each item produced in plants is guaranteed by Constraint (14). Constraints (15) and (16) ensure that inventory and capacity limits are considered. Finally, Constraints (17)-(23) define all decision variables' domains, i.e., the binary and continuous ones.

4. Uncertainty modelling

Due to changes in the business environment, uncertainty is inherent in the SC network design problem. According to Bairamzadeh et al. (2018), there are three types of uncertainties

(Randomness, Epistemic, and Deep uncertainty). Randomness occurs when there is enough data to estimate the probability distribution function of the parameter. Epistemic uncertainty applies to a condition in which there is a lack of knowledge in input data. It is generally provided in the type of judgmental data of linguistic attributes, and it may be gathered from experienced experts. Besides, deep uncertainty will occur when there is a lack of information about the related parameters (Bairamzadeh et al., 2018; Nayeri et al., 2020). There are several methods to cope with each of these types of uncertainty illustrated in Fig. 4.

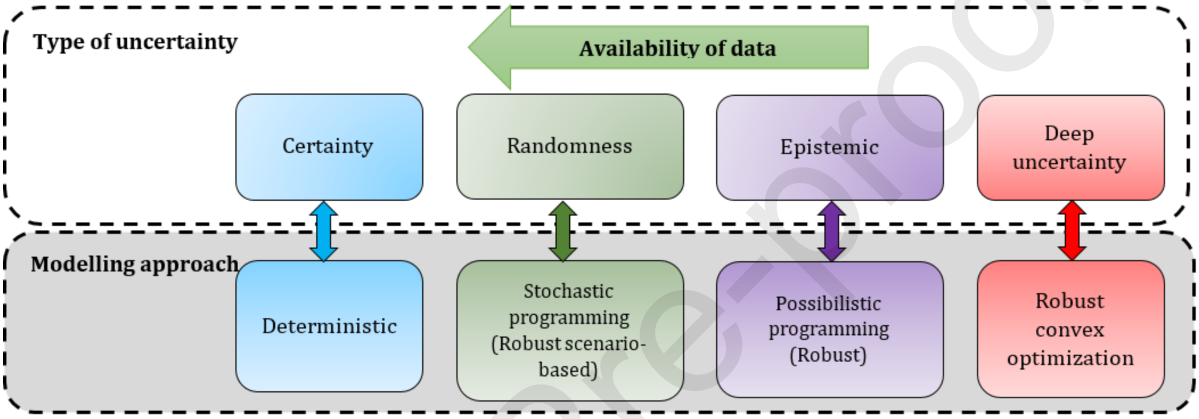


Fig. 4. Classifying different types of uncertainty and the methods to cope with them (Nayeri et al., 2020)

As it is shown in Fig.4, (robust) stochastic programming is applied to tackle randomness uncertainty, (robust) possibilistic programming is employed to deal with epistemic uncertainty, and robust convex optimization is used to cope with deep uncertainty. In this study, due to the research problem's condition, some historical data are available. However, there is a lack of knowledge in input data, and gathering data from experts is also needed. The robust fuzzy optimization approach, one of the branches of robust possibilistic programming, is therefore applied to tackle epistemic uncertainty.

The chance-constrained fuzzy programming model (CCFP) is a well-known posibilistic programing method for dealing with uncertainty. This method depends on some mathematics concepts, such as the fuzzy number expected value, the necessity (Nec), and the possibility (Pos). In this method, triangular and trapezoidal fuzzy numbers are employed (Talaei et al., 2016). For better understanding, to write the CCFP counterpart of the proposed model, the compact form of the proposed model is given below at first (when there is only one OF):

Model 2-1: Uncertain equivalent of SR-SCND

$$\boldsymbol{Min}\ E[Z] = \rho y + \tilde{\varsigma} x$$
$$s.t.$$
$$Ax \geq \tilde{d}$$
$$Bx = 0$$

$$Sx \leq Ny$$
$y \in \{0,1\}$, $x \geq 0$

Suppose that, vector ρ, coefficient matrices N and B, are crisp, and vectors $\tilde{\varsigma}$ and $\tilde{d}$ are uncertain parameters. In line with the literature (Nayeri et al. (2020), Talaei et al. (2016), Pishvaee et al. (2012), Pishvaee et al. (2012)), trapezoidal fuzzy numbers are applied in this study. The trapezoidal fuzzy numbers denote the uncertain parameters with four sensitive points (i.e., $\tilde{\theta} = \theta_{(1)}, \theta_{(2)}, \theta_{(3)}, \theta_{(4)}$) (see Fig. 5). Based on Talaei et al. (2016), if α_m shows the satisfaction level of constraints including uncertain parameters, the $CCFP$ programming model can be formulated as follows (where $g(\tilde{\varsigma}) = \frac{\varsigma_1 + \varsigma_2 + \varsigma_3 + \varsigma_4}{4}$):

Model 2-2: CCFP equivalent of Model 2-1

$Min\ E[Z] = \rho y + g(\tilde{\varsigma})x$

$Ax \geq (1 - \alpha_m)d_{(3)} + \alpha_m d_{(4)}$ $\quad \forall m$

$Bx = 0$

$Sx \leq Ny$

$0.5 \leq \alpha_m \leq 1$ $\quad \forall m$

$x \geq 0$

$y \in \{0,1\}$

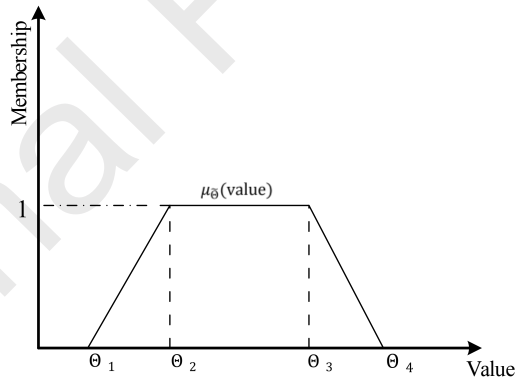


Fig. 5. Membership function of a trapezoidal fuzzy parameter $\tilde{\Theta}$ (Liu & Iwamura, 1998)

Based on the definitions above, the CCFP form of the proposed SR-SCND model is given below (all objectives are rewritten in minimization form):

$$\boldsymbol{Min}\ E[Z_1] = \sum_{m\in M}\sum_{l\in L} f^M_{ml}X^M_{ml} + \sum_{w\in W} f^W_w X^W_w + \sum_{m\in M}\sum_{t\in T}\phi^T_m K^M_{mt} + \sum_{w\in W}\phi^V_w K^W_w + \sum_{s\in S}\sum_{t\in T}\upsilon^S_{st}X^S_{st} + \sum_{w\in W}\sum_{c\in C}\upsilon^{WC}_{wc}X^{WC}_{wc} + \sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T} p^S_{rs}Q^{SM}_{rsmt} + \sum_{i\in I}\sum_{m\in M}\sum_{t\in T} p^M_{im}P_{imt} + \sum_{i\in I}\sum_{w\in W}\sum_{t\in T} h_i I^W_{iwt} + \sum_{i\in I}\sum_{c\in C}\sum_{t\in T}\pi_i L^C_{ict} + \sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T} g(\tilde{\tau}^S_s)\frac{\kappa^{SM}_{sm}}{\theta'_r q^S_{rs}}Q^{SM}_{rsmt} + \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A}\sum_{t\in T} g(\tilde{\tau}^A_a)\frac{\kappa^{MW}_{mw}}{\theta_i q^M_{i\cdots}}\cdots + \sum_{i\in I}\sum_{w\in W}\sum_{c\in C}\sum_{b\in B}\sum_{t\in T} g(\tilde{\tau}^B_b)\frac{\kappa^{WC}_{wc}}{\theta_i q^W_{ib}}Y^{WC}_{iwcbt} \quad (24)$$

$$\boldsymbol{Min}\ E[Z_2] = \sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T} g(\tilde{\rho}^S_s)\frac{\kappa^{SM}_{sm}}{\theta'_r q^S_{rs}}Q^{SM}_{rsmt} + \sum_{i\in I}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A}\sum_{t\in T} g(\tilde{\rho}^A_a)\frac{\kappa^{MW}_{mw}}{\theta_i q^M_{ia}}Y^{MW}_{imwat} + \sum_{i\in I}\sum_{w\in W}\sum_{c\in C}\sum_{b\in B}\sum_{t\in T} g(\tilde{\rho}^B_b)\frac{\kappa^{WC}_{wc}}{\theta_i q^W_{ib}}Y^{WC}_{iwcbt} \quad (25)$$

$$\boldsymbol{Min}\ E[Z_4] = g(\tilde{\Re}^T)\left[\sum_{r\in R}\sum_{s\in S}\sum_{m\in M}\sum_{t\in T}\frac{\left(g(\tilde{\vartheta}^S_{rs}) + \frac{g(\tilde{\xi}^{SM}_{sm})}{\theta'_r q^S_{rs}}\right)Q^{SM}_{rsmt}}{L^S_{rst}} + \sum_{i\in I}\sum_{l\in L}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A}\sum_{t\in T}\frac{\left(\vartheta^M_{ilm} + \frac{g(\cdots}{\cdots}\right.\cdots}{L^M_{i\cdots}} + \sum_{i\in I}\sum_{w\in W}\sum_{c\in C}\sum_{b\in B}\sum_{t\in T}\frac{\left(g(\tilde{\vartheta}^W_{iw}) + \frac{g(\tilde{\xi}^{CW}_{wc})}{\theta_i q^W_{ib}}\right)Y^{WC}_{iwcbt}}{L^W_{iwt}}\right] - \sum_{m\in M}\sum_{t\in T} g(\tilde{\Re}^M_m)K^M_{mt} - \sum_{w\in W} g(\tilde{\Re}^W_w)K^{\cdots}_{w\cdots} + \sum_{i\in I}\sum_{c\in C}\sum_{t\in T} g(\tilde{\Re}^D_c)L^C_{ict} \quad (26)$$

s.t.

$$L^C_{ict} + \sum_w\sum_b Y^{WC}_{iwcbt} \ge (1-\alpha)d_{ict_{(3)}} + \alpha d_{ict_{(4)}} \qquad \forall i\in I, \forall c\in C, \forall t\in T \quad (27)$$

$$0.5 \le \alpha \le 1 \quad (28)$$

Constraints (1)-(23)

Then, the roust counterpart of SR-SCND based on the proposed CCFP model can be formulated as follows:

Model 3: Robust SR-SCND model based on CCFP

$$\boldsymbol{Min}\ E[Z] + \eta\big(Z_{max} - E[Z]\big) + \pi\left(\sum_{i\in I}\sum_{c\in C}\sum_{t\in T} d_{ict_{(4)}} - (1-\alpha)d_{ict_{(3)}} - \alpha d_{ict_{(4)}}\right)$$

s.t.

$$L^C_{ict} + \sum_w\sum_b Y^{WC}_{iwcbt} \ge (1-\alpha)d_{ict_{(3)}} + \alpha d_{ict_{(4)}} \qquad \forall i\in I, \forall c\in C, \forall t\in T$$

$$0.5 \le \alpha \le 1$$

Constraints (1)-(23)

Where η and π signify coefficients that regulate the optimality robustness and the feasibility robustness of the solution vector, respectively (Talaei et al., 2016). Finally, Z_{max} (worst case scenario) is calculated using the 4th sensitive point of the uncertain parameters.

5. Solution method

The incorporation of experts' opinions significantly influences the efficiency of the model. The goal programming method, one of the efficient approaches for dealing with multi-objective models, defines each OF's aspiration level. The defined aspiration level is determined based on experts' opinions. In this research, the Multi-Choice Goal Programming with Utility Function (MCGP-UF) (Chang, 2011) is applied to solve the proposed multi-objective model. There are several reasons for applying the MCGP-UF as follows: (i) the MCGP method is one of the efficient approaches to solve multi-objective mathematical models, especially in the field of the supply chain problem that widely-used by researchers (e.g., Rostami et al. (2020), Yadollahinia et al. (2018), Razavi et al. (2020) and Jadidi et al. (2015)); (ii) this method considers the decision-makers' preference value (Nayeri et al., 2020); (iii) this method used a linear utility function that leads to solving the model more easily by common linear programming packages (Chang, 2011). The corresponding model is as follows:

Model 4: MCGP-UF to solve Robust SR-SCND model

$$Min \sum_k \left[w_k^d.\left(d_k^+ + d_k^-\right) + w_k^\xi.\left(\xi_k^-\right)\right]$$

$$s.t.$$

$$\lambda_k \le \frac{U_{k,max} - y_k}{U_{k,max} - U_{k,min}}$$

$$f_k(X) + d_k^- - d_k^+ = y_k$$

$$\lambda_k + \xi_k^- = 1$$

$$U_{k,min} \le y_k \le U_{k,max}$$

$$d_k^+, d_k^-, y_k, \lambda_k, \xi_k^- \ge 0$$

Model constraints set

Where y_k is a continuous decision variable, $U_{k,min}$ and $U_{k,max}$ show the range of kth objective aspiration level, d_k^- is the negative deviation, while d_k^+ is the positive deviation of $f_k(X)$ from y_k. ξ_k^- denotes the normalized deviation of y_k from $U_{k,min}$, w_k^ξ represents the weight of ξ_k^- and the utility value is signified by λ_k. In needed, the OFs in the model suggested by Chang (2011) can be normalized as below:

$$Min \sum_k \left[w_k^d.\left(\frac{d_k^+ + d_k^-}{f_k^- - f_k^+}\right) + w_k^\xi.\left(\xi_k^-\right)\right]$$

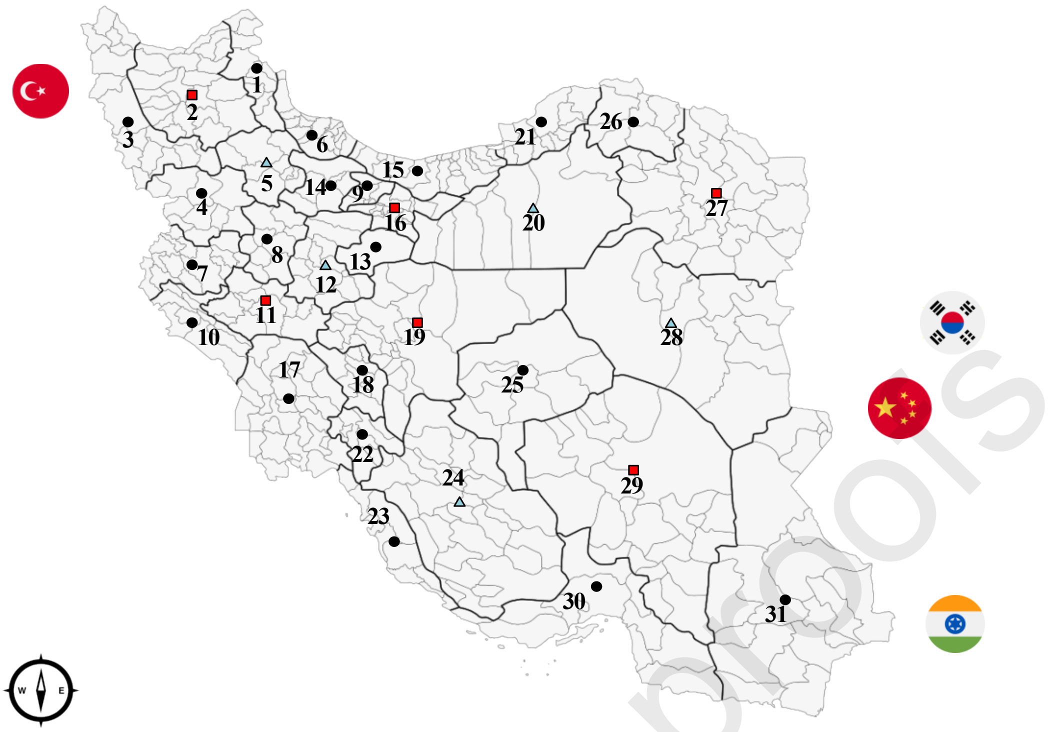
Where in minimization OF, $f_k^+ = \{\min f_k(X)\}$ and $f_k^- = \{\max f_k(X)\}$. ξ_k^- do not need to be normalized because of $0 \leq \xi_k^- \leq 1; \forall k$. Finally, the aspiration level ($[U_{k,min}, U_{k,max}]$) is calculated using the guide in Table 2.

Table 2. A guide for calculation aspiration levels using single objective programming (SOP) for kth objective (Nayeri et al., 2020)

Aspiration level	For Minimization objective(s)	For Maximization objective(s)
Solve SOP_k:	$Min\ Z_k$	$Min\ Z_k$
$U_{k,min}$ could be:	Equal to $Min\ Z_k$ is the best.	Equal to $Min\ Z_k$ or higher.
Solve SOP_k:	$Max\ Z_k$	$Max\ Z_k$
$U_{k,max}$ could be:	Equal to $Max\ Z_k$ or lower.	Equal to $Max\ Z_k$ is the best.

6. Case study

At the end of 2019, about 56 fatalities occurred in Iran due to the influenza epidemic (Presstv, 2019). Influenza viruses are among the most important respiratory pathogens globally that promote epidemic diseases, especially during cold seasons. The demand for influenza vaccine is experiencing a drastic growth in fall 2020 while the outbreak of the COVID-19 pandemic, which is hugely affecting millions of people worldwide (World Health Organization, 2020), has also occurred. Influenza is a public health problem that has important implications for health systems in different countries. All of this has led to rising health care costs, especially in Iran, as an important population center in West Asia. Having data from susceptible groups to the disease and demand estimation studies is one of the most important issues for health care policymakers in each country to select a specific population for vaccination (World Health Organization, 2012). By carrying out a case study in the Iranian pharmaceutical sector, a proper SC network for the influenza vaccine is suggested so that, in addition to being cost-effective, it contributes to social and environmental sustainability while responding to the needs of the population. Therefore, based on the health sector's data, the sustainable and resilient design and plan of the influenza vaccine SC is provided. Due to the lack of epidemiological data, potential demand points for this disease were identified using the research of Lim et al. (2012) on the Global Burden of Disease Study. In this regard, 20 out of 31 cities in Iran were considered as customer zones. A representation of the suppliers, candidate locations, and customer zones is provided in Fig. 6.



Legend

ID	City	ID	City	ID	City
1	Ardabil	11	Lorestan	21	Golestan
2	East Azerbaijan	12	Markazi	22	Kohgiluyeh & Boyer-Ahmad
3	West Azerbaijan	13	Qom	23	Bushehr
4	Kurdistan	14	Qazvin	24	Fars
5	Zanjan	15	Mazandaran	25	Yazd
6	Gilan	16	Tehran	26	North Khorasan
7	Kermanshah	17	Khuzestan	27	Razavi Khorasan
8	Hamadan	18	Chaharmahal & Bakhtiari	28	South Khorasan
9	Alborz	19	Isfahan	29	Kerman
10	Ilam	20	Semnan	30	Hormozgan
				31	Sistan & Baluchestan

Supply Chain Entities

Plant

Warehouse

Customer Zone

Fig. 6. Candidate vaccine production and distribution sites in Iran as well as suppliers (denoted by flag) and delivery points

6.1. Data setting

According to the Centers for Disease Control and Prevention (2020), there are three types of influenza vaccines, namely, Recombinant Flu Vaccine (RFV), Cell-based Flu Vaccine (CFV), and finally, Egg-based Flu Vaccine (EFV), which are beneficial to treat the disease. These vaccines are produced using several production technologies. The amounts of raw materials to make each item are provided by a biochemistry expert and shown in Table 3. Suppliers of raw material for the Iranian vaccine production industry are Turkey, South Korea, China, and India. To gain further information about model sets, crisp and fuzzy parameters, refer to Tables 4-6, in which parameters are estimated according to the influenza vaccine market in Iran (Iran Ministry of Health and Medical Education, 2020) as well as the opinions of three vaccine commerce specialists.

It should be noted that to define sensitive points of the trapezoidal fuzzy numbers, by inspiring Vahdani et al. (2013), we utilized the following way. At first, the most likely numbers (θ_2 and θ_3) are defined based on the corresponding probability distribution functions determined by experts. Afterward, a positive number r is determined by experts (decision-makers), and then pessimistic (θ_1) and optimistic (θ_4) values are calculated as follows:

$$\theta_1 = \theta_2 - r$$

$$\theta_4 = \theta_3 + r$$

Table 3. Percentage of raw materials required for producing of each vaccine

Raw material ($\boldsymbol{r}$)	**Vaccine ($\boldsymbol{i}$)**	**1**	**2**	**3**
	Name	**RFV**	**CFV**	**EFV**
1	Baculo virus	15%	0%	0%
2	Hemagglutinin	8%	0%	0%
3	Animal's Cell Virus	0	15%	0%
4	Hen's Egg Virus	0	0%	16%
5	Antibiotic	20%	20%	20%
6	Gelatin	10%	15%	15%
7	Thimerosal	18%	15%	14%
8	Aluminum salts	12%	19%	18%
9	Formaldehyde	17%	16%	17%

Table 4. Scale of problem

Sets	$\mathbb{S}$	$\mathbb{M}$	$\mathbb{W}$	$\mathbb{C}$	$\mathbb{R}$	$\mathbb{I}$	$\mathbb{L}$	$\mathbb{A}$	$\mathbb{B}$	$\mathbb{T}$
Size	4	6	5	20	9	3	5	3	2	4

Table 5. Certain parameters

Parameter	Value	Parameter	Value	Paramet er	Value
δ_{rsm}	1	L^S_{rst}	$\sim U(8,10)$	$\hbar_i$	$\sim U(0.011,0.033)/i$
θ_i	0.05	L^M_{imt}	$\sim U(10,15)$	π_i	$\sim U(0.033,0.066)/i$
θ'_r	0.1	L^W_{iwt}	$\sim U(5,7)$	ϱ_{ic}	$\sim U(0.2,0.3)/i$
q^S_{rs}	100	f^M_{ml}	$\sim U(12,15) \cdot 10^6 \cdot l$	ϖ_{ml}	$\sim U(0.5,0.9)/l$
q^M_{ia}	25	f^W_w	$\sim U(10,12) \cdot 10^6$	p^S_{rs}	$\sim U(0.04,0.1)$
q^W_{ib}	12.5	υ^S_{st}	$\sim U(1.5,12) \cdot 10^4$	p^M_{im}	$\sim U(0.1,1)/i$
k_{rs}	$\sim U(11000,15000)$	υ^{WC}_{wc}	$\sim U(1,1.5) \cdot 10^4$	ϕ^V_w	$\sim U(0.0525,0.21)$
K'^{Max}_w	$\sim U(250,300) \cdot \lvert\mathbb{C}\rvert \cdot \lvert\mathbb{I}\rvert$	ϑ^M_{ilm}	$\sim U(5,8) \cdot 10^{-4}/l$	ϕ^T_m	$\sim U(0.21,0.84)$
K'^{Min}_w	$\sim U(100,150) \cdot \lvert\mathbb{C}\rvert \cdot \lvert\mathbb{I}\rvert$	M	10^9		
K^{Max}_{mt}	$\sim U(38.7,47.7)$	K^{Min}_{mt}	$\sim U(29.7,38.7)$		

** Note:*
The units of parameters are the same as that of notations in Section 3.1.

Table 6. Uncertain parameters ($\tilde{\Theta}$)

Parameter	Triangular Fuzzy numbers			
	$\Theta_{(1)}$	$\Theta_{(2)}$	$\Theta_{(3)}$	$\Theta_{(4)}$
$\tilde{d}_{ict}$	$\sim U(100,150)$	$\sim U(150,200)$	$\sim U(200,250)$	$\sim U(250,300)$
$\tilde{\vartheta}^{S}_{rs}$	$\sim U(1,1.5) \cdot 10^{-4}$	$\sim U(1.5,2) \cdot 10^{-4}$	$\sim U(2,2.5) \cdot 10^{-4}$	$\sim U(2.5,3) \cdot 10^{-4}$
$\tilde{\vartheta}^{W}_{iw}$	$\sim U(1,3) \cdot 10^{-4}$	$\sim U(3,5) \cdot 10^{-4}$	$\sim U(5,7) \cdot 10^{-4}$	$\sim U(7,9) \cdot 10^{-4}$
$\tilde{\xi}^{SM}_{sm}$	$\sim U(4,4.5)$	$\sim U(4.5,5)$	$\sim U(5,5.5)$	$\sim U(5.5,6)$
$\tilde{\xi}^{MW}_{mw}$	$\sim U(6,6.5)$	$\sim U(6.5,7)$	$\sim U(7,7.5)$	$\sim U(7.5,8)$
$\tilde{\xi}^{WC}_{wc}$	$\sim U(1,1.5)$	$\sim U(1.5,2)$	$\sim U(2,2.5)$	$\sim U(2.5,3)$
$\tilde{\tau}^{S}_{s}$	$\sim U(0.4,0.8) \cdot s$	$\sim U(0.8,1.2) \cdot s$	$\sim U(1.2,1.6) \cdot s$	$\sim U(1.6,2) \cdot s$
$\tilde{\tau}^{A}_{a}$	$\sim U(0.2,0.4)/a$	$\sim U(0.4,0.6)/a$	$\sim U(0.6,0.8)/a$	$\sim U(0.8,1)/a$
$\tilde{\tau}^{B}_{b}$	$\sim U(0.2,0.4)/b$	$\sim U(0.4,0.6)/b$	$\sim U(0.6,0.8)/b$	$\sim U(0.8,1)/b$
$\tilde{\rho}^{S}_{s}$	$\sim U(1,2) \cdot s$	$\sim U(2,3) \cdot s$	$\sim U(3,4) \cdot s$	$\sim U(4,5) \cdot s$
$\tilde{\rho}^{A}_{a}$	$\sim U(8,10)/a$	$\sim U(10,12)/a$	$\sim U(12,14)/a$	$\sim U(14,16)/a$
$\tilde{\rho}^{B}_{b}$	$\sim U(8,10)/b$	$\sim U(10,12)/b$	$\sim U(12,14)/b$	$\sim U(14,16)/b$
$\tilde{\mathfrak{R}}^{T}$	4	5	6	7
$\tilde{\mathfrak{R}}^{M}_{m}$	$\sim U(5,6)$	$\sim U(6,7)$	$\sim U(7,8)$	$\sim U(8,9)$
$\tilde{\mathfrak{R}}^{W}_{w}$	$\sim U(4,5)$	$\sim U(5,6)$	$\sim U(6,7)$	$\sim U(7,8)$
$\tilde{\mathfrak{R}}^{D}_{c}$	$\sim U(600,700)$	$\sim U(700,800)$	$\sim U(800,900)$	$\sim U(900,1000)$

** Note:*
The units of parameters are the same as that of notations in Section 3.1.

6.2. Model validation

Concerning different aspects of SCs (e.g. sustainability and resilience) as well as their diverse structures (location of entities, distances, etc.) and types of their operations and services, it is highly challenging to derive insights by developing a universal model. Accordingly, based on some justified assumptions, the problem's scope is reduced for the proposed model to be tested on a case/numerical study with real data and checked for the validity of its objectives and constraints. In this section, the presented MCGP-UF model is therefore solved using the proposed case study data to demonstrate its applicability and validity. The model's optimal solution provides supportive decisions that lead to an increase in the influenza vaccine SC's sustainability and resiliency, including strategic and tactical variables, representing its network design and the service plan. It also helps provide a business continuity management strategy and evaluates the inventory, production, capacity variables under real-world uncertainties. Finally, considering probable changes in the model parameters, the analyses and corresponding results for the proposed problem are presented. It should also be noted that the model is coded in GAMS (version 29.1.0) and solved by the ILOG CPLEX solver on a Laptop with a 2.4 GHz Intel® 5500U processor and 8 GB of RAM.

According to the guidelines provided in Table 2, the payoff table should be derived in the first step. However, according to the terms in goal 3 (OF3), the minimum and maximum aspiration level of the terms in the social objective should be calculated first. The corresponding payoff values are illustrated in Tables 7 and 8. As mentioned before, all objectives were rewritten in the minimization form. Besides, it is revealed that reaching the optimal value of a goal leads to higher values for the other goals, which is not desired by the decision-maker. Respectively, appropriate weights of goals are selected, according to the expert's opinion ($w_k^d = w_k^\xi = 0.25, \forall k\ and\ \omega_1 = \omega_2 = 0.5$).

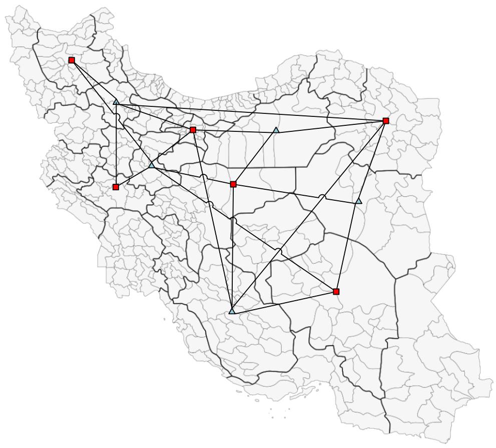
Table 7. Payoff table of the social objective terms when $\eta = 0.5, \pi = 10000$, and $\alpha^* = 1$

	Sub-Goal 1: Social welfare	**Sub-Goal 2: Deprivation**
U_{min}	1063.910	0
U_{max}	7353.033	3768.593

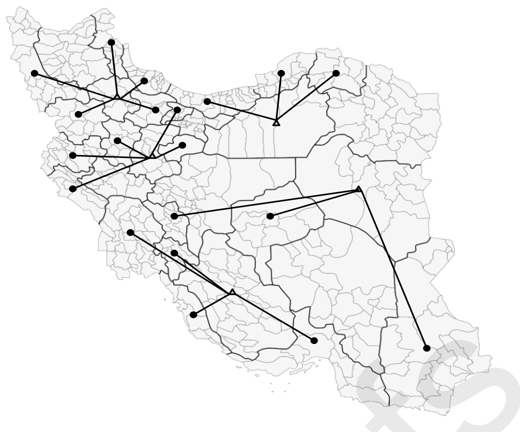
Table 8. Payoff table of the multi-objective optimization problem when $\eta = 0.5, \pi = 10000$, and $\alpha^* = 1$

Solve	**Goal 1: Economic**	**Goal 2: Environmental**	**Goal 3: Social**	**Goal 4: Resilience**
SOP_1: Min Goal 1	1.745679E+8	2.303486E+8	1	2.207745E+8
SOP_2: Min Goal 2	2.831867E+8	6.603864E+7	0.777	2.970476E+8
SOP_3: Min Goal 3	1.94588E+10	4.56976E+10	0.014	7.661882E+7
SOP_4: Min Goal 4	3.701448E+8	3.642437E+8	0.132	1.212450E+7
U_{min}	1.745679E+8	6.603864E+7	0.014	1.212450E+7
U_{max}	1.94588E+10	4.56976E+10	1	2.970476E+8

In the next step, the MCGP-UF model is solved using the lower and upper bounds (aspiration levels) for the four goals. According to the results, the optimal network of the vaccine SC is depicted in Fig. 7. As can be seen, all of the plants and warehouses are established. It should be noted that since all suppliers are also selected to serve all of the plants over the desired activity horizon (1 seasonal-year), the supply network is not depicted. Regarding this network configuration, the optimum goal values are $Z_1^* = 8.048050E + 8, Z_2^* = 1.280270E + 9, Z_3^* = 0.018\ and\ Z_4^* = 1.083194E + 7$. These values are calculated while the optimal confidence level of the CCFP model is equal to 1.



a) Production network



b) Distribution network

Fig. 7. The optimum influenza vaccine SC network under base investigation

Tables 9 and 10 report the overall capacity of the warehouses and the seasonal capacity of the production plants, respectively. The ID associated with each warehouse/plant determines the city where it needs to be established. Also, lost sales were set to 105.356 L for ID 25 of egg-based vaccine, and South Khorasan (ID 28) is decided to hold no inventory during the seasons.

Table 9. The overall capacity of warehouses (L)

Warehouse	**ID 5**	**ID 12**	**ID 20**	**ID 24**	**ID 28**
Capacity	16781.868	17168.157	16884.746	16391.394	16239.921

Table 10. The seasonal capacity of the plants (L)

Plant	Technology level	Season			
		1	2	3	4
ID 2	3	40.236	44.402	45.644	43.825
ID 11	1	41.726	43.998	43.870	43.591
ID 16	4	38.949	45.999	41.210	42.600
ID 19	2	43.903	47.495	41.593	45.567
ID 27	2	40.633	40.266	45.281	41.131
ID 29	5	47.363	47.241	41.003	41.625

As the supply chain network design problem is known as an NP-Hard one, to provide a discussion on the complexity of the model, 15 test problems in different sizes (ranging from small-sized to large-sized) are solved considering three gap levels (0%, 20%, and 40%) from the optimal solution. The obtained results are presented in Appendix A, Table A.14. This table only discusses the number of binary variables, continuous variables, and constraints, while it should be noted that the complexity of the problem depends not only on the numbers of decision variables and constraints but also on the data structures that we implement. The distribution of the applied parameters is the same as the case study. The characteristics of the test problems (scale and number of binary and continuous variables and constraints) are reported in Table A.13. According to Table A.14, the ILOG CPLEX solver in GAMS 29.1 optimization software fails to find the last four test problems' optimal solutions in 20000 seconds. Such obstacles can be addressed by setting a particular deviation tolerance ($GAP = \frac{Obtained\ value - Optimal\ value}{Optimal\ value}$) from the optimal solution so that a near-optimal answer is obtained within an acceptable computational time. For example, by allowing a 20% gap from the optimal solution (set option optca=0.2, optcr=0.2 in GAMS), test problems 12 and 13 can be solved in less than 20000 seconds and increasing this gap to 40% (set option optca=0.4, optcr=0.4 in GAMS) results in solving test problems 14 and 15 over this time as well.

Moreover, Table A.14 reveals that as the problem size increases, the CPU time rises drastically, which leaves the decision-makers with two choices. On the one hand, since the proposed model aims to make several strategic decisions (e.g., supplier selection, transportation selection, facilities location, and technology selection), the computational time of the problem is not of high importance, and decision-makers may prefer to wait longer to get the optimal answer which is also practical for several years.

On the other hand, some decision-makers favor a fast-approximate solution over an accurate answer with high CPU time. This group usually applies heuristic or metaheuristic algorithms to find their preferable answer.

6.3. Sensitivity analysis

In this section, the impact of change in important parameters for all four OFs is further analyzed. In accordance with the previous section, sensitivity analysis can aid generalizing the results in other cases based on changing the values of the model parameters.

6.3.1. Change in demand value

Under eight different scenarios, demand deviated (i.e., 10, 20, 30, 50 percent positive and negative deviations) to analyze proposed SC performance indicators' behavior. The analysis results are shown in Fig. 8, in which social responsibility and resiliency goals are redefined by social impact and SC's vulnerability value.

As illustrated by Fig. 8, when demand either increases or decreases from its default value, the Economic and Environmental OFs, reach a better value. It may be because the problem considers a level of robustness for the base value in the CCFP model (which is equal to 0.5). Moreover, it can be inferred that the social impact OF increases steadily as demand increases. This may be because the value of the lost sales, because of systems constrained capacity, increases. However, after a point (about 30% increase in demand) as environmental and economical OFs begin to increase, the increased redundancy in the system's production capacity may help reach a lower value for social OF.

The abovementioned results do not repeat for vulnerability OF. As shown by Fig. 8, as demand increases, the system tends to be more vulnerable to future risks due to lack of proper capacity and/or lost sales that may occur regarding maximum warehouse capacity. The rate of this increase is low when the rise in demand is below 30%. However, the rate of growth is linear wise after passing the 30% increase point. This phenomenon implies that as flows start to be n larger volumes, the lead time ratio between consecutive mutual entities may reach values closer to 1.

Finally, Fig. 9 illustrates an increase or decrease that the capacity of whole manufacturing components and warehousing ones may experience. As can be seen, both capacities are increased as the demand changes up to 60%. However, this change is stable as demand reaches high levels (greater than 30% for manufacturing and greater than 20% for warehousing entities). This stability is better for warehousing entities than the manufacturing ones, as manufacturing centers may also undergo an extra increase as demand reaches levels 50-60% higher than the demand's base level.

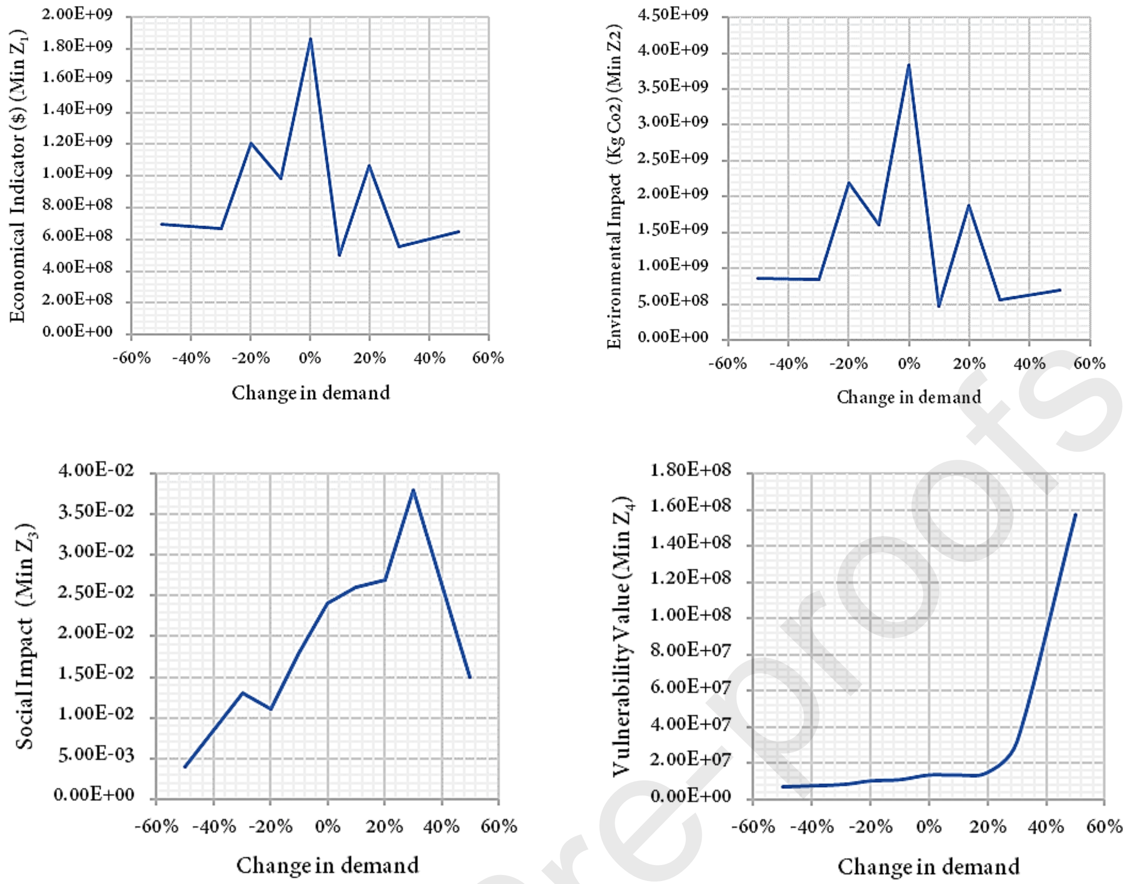


Fig. 8. The impacts of deviation in demand from the base case

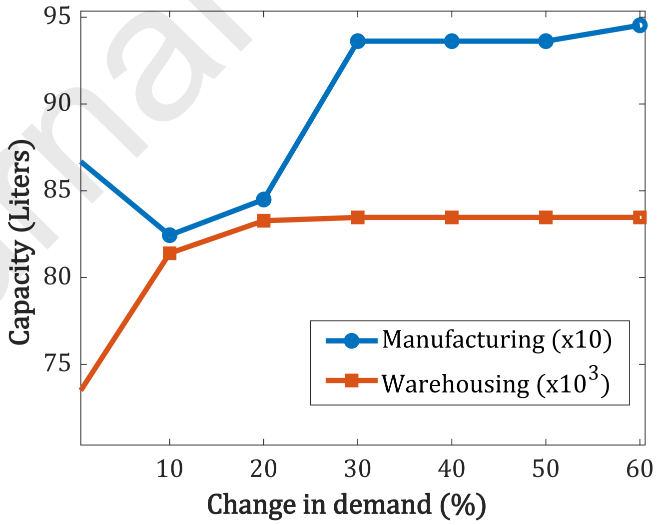


Fig. 9. The impacts of an increase in demand from the base case on the overall capacity of the SC

6.3.2. Change of feasibility robustness

As shown in Table 11, changes in π negligibly affect the OFs. The minimum satisfaction level remains constant and equal to 1, as well.

Table 11. Sensitivity analysis on weight coefficient (π), when $\eta = 0.6$

$\pi = 1000$		$\pi = 10000$		$\pi = 100000000$	
Run time (s)	29.351	Run time (s)	63.194	Run time (s)	33.212
Goal 1: Economic	1.038711E+9	Goal 1: Economic	1.038711E+9	Goal 1: Economic	1.038711E+9
Goal 2: Environmental	1.714969E+9	Goal 2: Environmental	1.714969E+9	Goal 2: Environmental	1.714969E+9
Goal 3: Social	0.018	Goal 3: Social	0.018	Goal 3: Social	0.018
Goal 4: Vulnerability	1.534173E+7	Goal 4: Vulnerability	1.534173E+7	Goal 4: Vulnerability	1.534173E+7
α	1	α	1	α	1

6.3.3. Change of optimality robustness

Here, the optimality robustness of the Robust SR-SCNFD model based on the optimality robustness parameter η is analyzed. As clearly seen from Table 12, when η increases from 0.3 to 0.9, the model goals try to get values closer than to the Z_{max}, i.e., the worst-case scenario, when the trapezoidal fuzzy numbers have their worse value, either $\tilde{\Theta}_1$ (underestimation) or $\tilde{\Theta}_4$ (overestimation), regarding the direction of the mathematical model and the term, which includes uncertain parameters. Meanwhile, the value of the social goal does not change significantly. In total, the run time of the model can experience an increase when the robust value is met.

Table 12. Sensitivity analysis on weight coefficient (η), when $\pi = 10000$

$\eta = 0.3$		$\eta = 0.6$		$\eta = 0.9$	
Run time (s)	84.083	Run time (s)	49.199	Run time (s)	84.320
Goal 1: Economic	4.550195E+8	Goal 1: Economic	1.038711E+9	Goal 1: Economic	1.63053E+09
Goal 2: Environmental	4.067807E+8	Goal 2: Environmental	1.714969E+9	Goal 2: Environmental	2.97556E+09
Goal 3: Social	0.023	Goal 3: Social	0.018	Goal 3: Social	0.019
Goal 4: Resilience	1.306491E+7	Goal 4: Resilience	1.534173E+7	Goal 4: Resilience	1.70254E+07
α	1	α	1	α	1

The concept of robustness price is defined as the value that an objective reaches its worst-case and getting more deviated from its optimal value (in this case, minimum). Therefore, the robustness price increases as the optimality robustness controller get closer to the 1.

6.3.4. Change in weight of goals

In this section, an analysis of the change in objective weights is done to estimate the Pareto front based on the defined goals. Fig. 10 depicts the derived results. As seen, many points from the non-convex part of the objectives cannot be extracted using this approach (Das and Dennis, 1997). Overall, it can be concluded that goals are conflicting in nature, and with a decrease in one goal, the other goal is increased and gets deviated from its aspiration level.

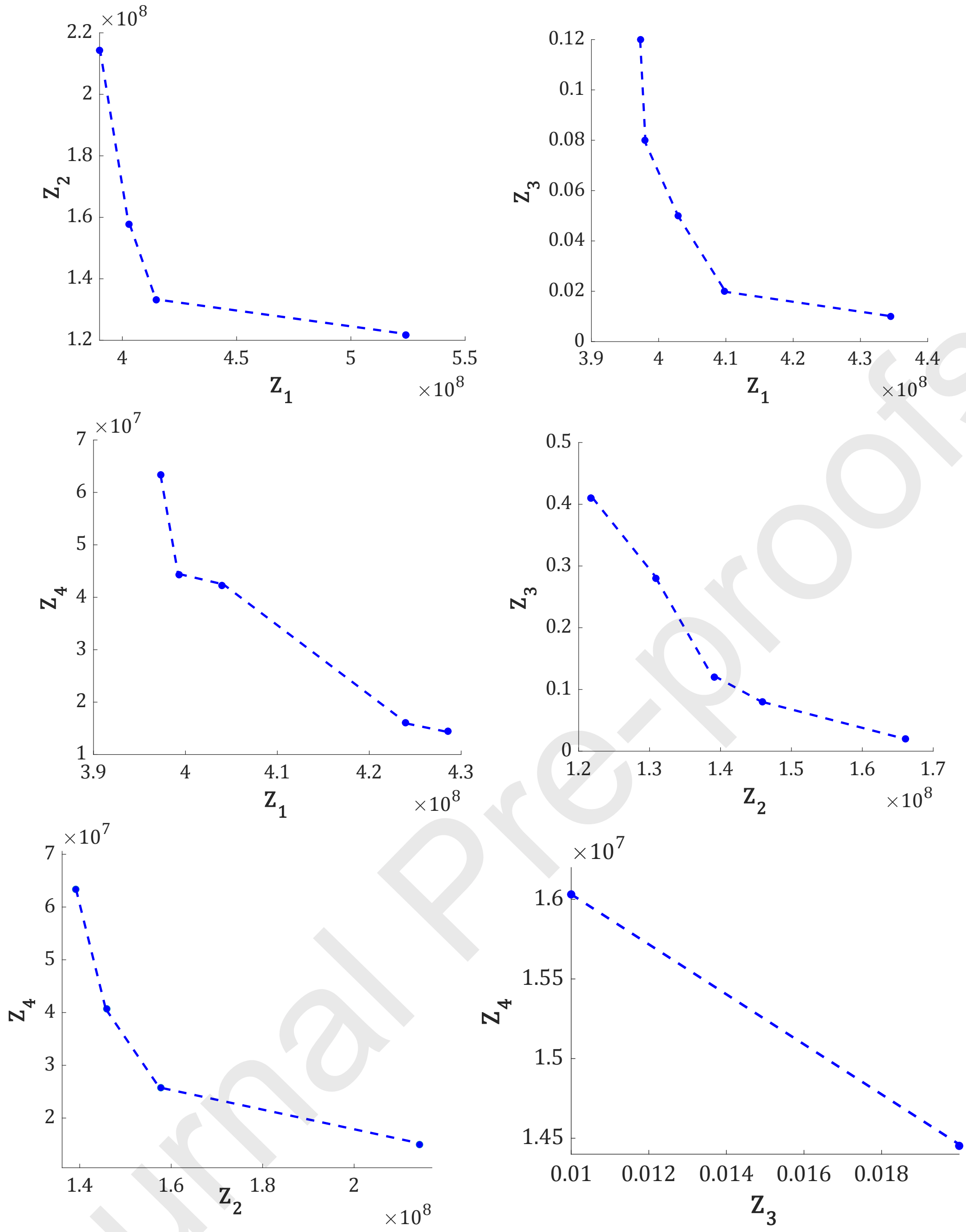


Fig. 10. Estimated Pareto fronts by the change of w_k^d for all goals

7. Insights and analytics

From the case study implemented, it can be concluded that SC neither should be planned nor designed without integrated consideration of sustainability and resilience performance measures, which are necessities for viability in today's competitive business environments. The findings validate consideration of capacity planning as an imperative action plan for managers when optimizing such multi-dimensional performance measures to maintain efficiency, primarily when the surge of demand occurs. Notably, as the results indicate, SC managers should consider a uniformly distributed capacity among manufacturing and warehousing facilities. Such a conclusion is not seen in previous researches as it is usually accounted for *discrete* capacity levels for the entities involved in an SC (e.g., see Zahiri et al. (2017)). This is probably due to impossibility of using intermediary values for these levels in such models. Notably, usage of such analysis, i.e., "continuous capacity tracking" and "possible capacity expansions" were suggested by previous studies in the field (Ivanov, 2018; Jabbarzadeh et al., 2018) to derive more insights according to the interplay that sustainability and resiliency OFs may have.

Moreover, with an increase in demand (e.g., due to societal anxiety), managers usually tend to increase their inventory level, or alternatively, warehousing capacity, while neglecting the dramatic impact of the operational performance's manufacturing capacity. This study recommends a rise in manufacturing and warehousing capacity and with the same rate, especially at high demand levels (Fig. 8). By such a policy, the whole of SC is more resilient to demand-side fluctuations, especially at the time of disasters. According to this study, capacity planning can be used in various industrial fields (in retail, automotive, health, etc.) to improve sustainability and resilience. Some other noticeable suggestions are summarized as follows:

- Operational features such as deviation in demand may positively impact SC's performance, either economically or environmentally. Like Klibi and Martel (2012), it can be concluded that cost reductions and even revenues are possible to occur by providing items required by customers under demand surge events. However, in contrast with Mari et al. (2014), an economical supply chain can also be lowlily vulnerable to the risks.
- Mostly, the vulnerability of the system increases as the demand increases. It applies to the cases when the SCs face a sudden surge of demand during their activity period in the future (such as COVID-19 vaccine production). Therefore, to be more resilient on the demand-side, the SC should be planned carefully with a proper capacity increase in manufacturing and warehousing centers (however, at the same rate as shown in Fig. 9). Notably, redundancy

policies not always make the SC resilient toward disruptions, as stated generally by Sheffi (2006). However, it would be possible to hold extra inventory to cover part of the demands in some surge scenarios (Mousazadeh et al., 2015).

- In the case of demand surges, the firm should not be anxious about the rise in all future scenarios' total costs. Instead, concerns about the lost sales, which decrease the firm's social responsibility level, rise. This issue is new and one of the most critical performance measure, which should be emphasized during resilience planning. It is in line with Mari et al. (2014), where it is stated that reaching sustainability leads to reductions in vulnerabilities.
- When sporadic and low volume demands are met, the resiliency measure stays at an optimum level. Still, there will be increases in both economic and environmental indicators (due to proactive strategy). Similar to previous studies, demand has the most significant effect on the costs, environmental impacts, and capacity of SC entities (Yılmaz Balaman & Selim, 2016).
- Finally, the findings magnify the importance of uncertainty in the SR-SCND problem (similar to Zahiri et al. (2020)). That is, the higher the robustness price (e.g., deviation from ideal economic goals), the higher chance that the manager can ensure the optimality of the proposed SR-SCND problem's decisions.

8. Conclusion

This research made an effort to develop a mathematical model for a variant of the SR-SCND problem that includes three echelons (i.e., the supplier, manufacturing plants, and warehouse entities). The sustainability objectives were to minimize the total costs (the economic aspect of a sustainable SC), CO2 emissions rate (the environmental impact of a sustainable SC), and maximize CSR by reducing lost sales and increasing accessibility to order fulfillment points as well as job creation (the social aspect of a sustainable SC), respectively. The resiliency objective evaluates the SC's vulnerability to various risks by taking measures, namely capacity redundancy, lead time ratio, and customer de-service level, into account. Moreover, a robust fuzzy programming method was used to deal with uncertainties in the input data related to a real-world SC of influenza vaccine in Iran. This vaccine's demand is witnessing a conspicuous rise due to the newly-emerged COVID-19 pandemic in the year 2020. Finally, the problem under study was solved by the MCGP-UF approach. Some managerial insights were also derived according to the analysis of crucial parameter effects on the objectives. The insights suggest that firms should jointly reconsider warehousing and manufacturing capacities, plan for an increase of their CSR performance, and proactively plan for future demand surges to act competitively, especially in disastrous future scenarios.

Since the presented model is amongst the primitive efforts made in this field, several future research suggestions can help to fill the gap. One direction can be the consideration of items' perishability impacts on SR-SCND models. The other one can be studying different types of uncertainties such as box, ellipsoidal, and polyhedral in a robust optimization framework and compare them with this paper. Moreover, the resiliency of the SC in the future may be analyzed both proactively and reactively. Also, developing metaheuristic or heuristic algorithms to solve the research problem in large-sized instances is another direction for future research.

Appendix A. Characteristics and results of test problems

Table A. 13. Characteristics of test problems

Test Problem	Set Size S, M, W, C, I	No. of Constraints	No. of Continuous Variables	No. of Binary Variables
1	1, 3, 2, 10, 1	356	517	41
2	1, 4, 3, 10, 1	447	773	57
3	3, 4, 3, 15, 2	991	1,975	80
4	3, 5, 4, 15, 2	1,227	2,667	101
5	4, 5, 4, 20, 3	1,716	4,531	125
6	4, 6, 5, 20, 3	2,031	5,783	151
7	6, 6, 5, 25, 4	2,855	8,907	184
8	6, 8, 7, 25, 4	3,715	13,043	246
9	8, 8, 7, 30, 5	4,809	18,269	289
10	8, 10, 9, 30, 5	5,899	24,567	361
11	11, 10, 9, 35, 7	7,937	37,504	418
12	11, 13, 12, 35, 7	10,079	53,299	541
13	14, 13, 12, 40, 9	12,704	73,939	613
14	14, 16, 15, 40, 9	15,353	97,987	751
15	17, 16, 15, 45, 10	18,103	117,401	838

Table A. 14. Performance of the proposed MCGP-UF method for test problems

Test Problem	GAP 0%					GAP 20%	GAP 40%
	OFV1	OFV2	OFV3	OFV4	CPU Time (s)	CPU Time (s)	CPU Time (s)
1	3104505E+8	4019112E+8	0.002	3847909E+6	5	2	1
2	3817937E+8	5973150E+8	0.005	5412271E+6	41	33	18
3	4084150E+8	6645224E+8	0.009	6535132E+6	139	110	63
4	6491223E+8	8643198E+8	0.011	7109064E+6	304	245	157
5	7232512E+8	1036521E+9	0.016	9248780E+6	531	429	238
6	8048050E+8	1280270E+9	0.018	1083194E+7	992	795	510
7	1019426E+9	2515769E+9	0.024	2802326E+7	1680	1342	981
8	1577808E+9	3171902E+9	0.039	3175470E+7	3327	2661	1596
9	2985361E+9	4264136E+9	0.063	4529844E+7	7055	5648	2333
10	3315113E+9	5907293E+9	0.071	4941615E+7	10614	8491	3068
11	5030109E+9	7618800E+9	0.088	7286638E+7	14111	11087	5652
12	-	-	-	-	>20000	15643	8385
13	-	-	-	-	>20000	19522	12713
14	-	-	-	-	>20000	>20000	14713
15	-	-	-	-	>20000	>20000	19814

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Highlights

- Designing a sustainable- resilient supply chain network under uncertainty.
- Interactions and mutual effects of sustainability and resiliency on strategic, tactical and operational decisions are discussed.
- A real case study is investigated in this research.
- Sensitivity analysis and the managerial suggestions are provided.