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Research Article

Decision-making approach based on time series to configure a responsive and sustainable supply chain considering different transportation modes under uncertainty

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Abstract

The importance of logistics activities in the nowadays modern and competitive marketplace has attracted the attention of researchers toward the supply chain management (SCM) problem. Also, by increasing environmental and social concerns, the concept of sustainability has been drastically highlighted in today's logistics networks. Therefore, the current study focuses on designing a closed-loop supply chain based on the sustainability and responsiveness dimensions by considering different transportation modes using a data-driven model. In this research, at the outset, a mathematical model is proposed to optimize the sustainability dimensions by considering the responsiveness metric. Then, since the dynamic nature of the business environment leads to the high level of uncertainty, we combine the SARIMA (Seasonal Autoregressive Integrated Moving Average) and the Possibilistic Robust Stochastic (PRS) methods to develop a data-driven framework for tackling the mixed uncertainty. Afterward, by considering the medical equipment industry as a real-world application, a heuristic-based meta-goal programming (MGP) method is developed to solve the proposed model. The achieved results show the appropriate performance of the proposed data-driven model and it has estimated the parameters with over 90% accuracy across all scenarios. Afterward, a series of sensitivity analyses are performed to evaluate how key model parameters influence the research problem, leading to the generation of relevant managerial insights. For example, it has been observed that an increase in the level of services leads to a rise in greenhouse gas emissions. Additionally, social factors increase as the level of services rises.

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1. Introduction

In today's challenging marketplaces, the importance of logistics and Supply Chains (SCs) has become more prominent. Nowadays, managers of organizations and enterprises know that to maintain their market share and subsequently increase profits, they need to set up a suitable plan to optimize their supply chain (Bai et al. 2024; Nayeri et al. 2022). Therefore, in the three last decades, the focus of researchers and managers has been significantly attracted toward the SC Management (SCM) problem, and several articles have been conducted in this area. In this field, one of the crucial branches of SCM is the SC network design (SCND), in which managers and researchers seek to make various decisions, such as long-term and mid-term decisions. In traditional problems, the main focus of managers and researchers was on the financial aspects. However, in recent years, owing to enhancing environmental and social concerns, the concept of a sustainable supply chain has become a trend topic, which attempts to incorporate the environmental, financial, and social dimensions into the research issue (Najafi and Zolfagharinia 2024; Sheykhzadeh et al. 2024). Considering the elements of sustainable development in the supply chain may seem like an additional cost at a glance, however, it can significantly enhance the customers' satisfaction and subsequently their loyalty, which increases the total profits in the long term (Sazvar et al. 2022; Sazvar, Tafakkori, et al. 2021). Hence, incorporating the sustainability pillars is a necessary issue in the SCM problems.
One of the well-known concepts in the recent research papers is responsiveness. Generally, responsiveness is the capability of a supply chain to satisfy the requirements of customers within a planning period (Javan-Molaei et al. 2024; Rabbani et al. 2018; Saisridhar et al. 2024). There are several real-world examples that demonstrate the crucial impact of the responsiveness concept in the marketplace. For instance, in 1994, the market share of Motorola company (a cell phone producer in the U.S.) was equal to 60%. However, on 2002, since this company could not respond to the growing and changing customer demands, its market share fell to 13% (Li et al. 2023; Nayeri, Torabi, et al. 2021). Therefore, ignoring the responsiveness concept in the supply chain may result in irreparable losses.
One of the industries whose key role has been significantly influenced by COVID-29 outbreak is the Medical Equipment (ME) industry (ForouzeshNejad 2022; Nayeri et al. 2023; Rostami et al. 2023). ME are part of the healthcare systems that have played a critical role in improving healthcare services during the latest pandemic. Since the demand for ME has significantly increased during the COVID-19 pandemic, the related managers have faced several major challenges in logistics activities. Therefore, investigating the logistics activities of the ME industry can significantly help managers to improve the efficiency and productivity of this crucial industry.
As mentioned, this study seeks to explore the SCND problem in relation to the sustainability and responsiveness concepts for the ME industry. To this end, this research provides a data-driven decision-making approach to design a Closed-Loop SC Network (CLSCN), in which a Multi-Objective Model (MOM) is proposed for the optimal configuration of the network and then employed a Data-Driven PRS (DDPRS) method to deal with the mixed uncertainty. In this regard, first, the PRS counterpart is proposed for the research problem and then SARIMA method is employed to estimate the value of critical parameters of the model (e.g., demand). Finally, the suggested model is solved using a heuristic-based goal programming method. Moreover, since the ME have played a significant role during the Coronavirus outbreak, the current study chooses this industry to demonstrate the real-world application of the proposed model. The overall structure of the research is shown in Figure 1, consisting of four main steps. In the first step, the mathematical model of the problem is designed. Then, an approach to address uncertainty is developed, and in the third step, key parameters are estimated using a data-driven algorithm. In the fourth step, the model is solved.
In summary, the development of a data-driven model for close loop supply chain network (CLSCN) represents the main innovation of this study, where key parameters with uncertainties are estimated using data-driven algorithms, enhancing the model's decision-making accuracy. Additionally, simultaneously considering resilience and sustainability under uncertainty in CLSCN can be regarded as another innovation of this research. From a case study perspective, incorporating two products from medical equipment into the model is a topic that has been rarely explored in the literature.
In this study, Section 2 is focused on reviewing the literature. Section 3 presents the methodology of the research problem. Section 4 provides the numerical results. Finally, Section 5 presents the conclusions and future suggestions.

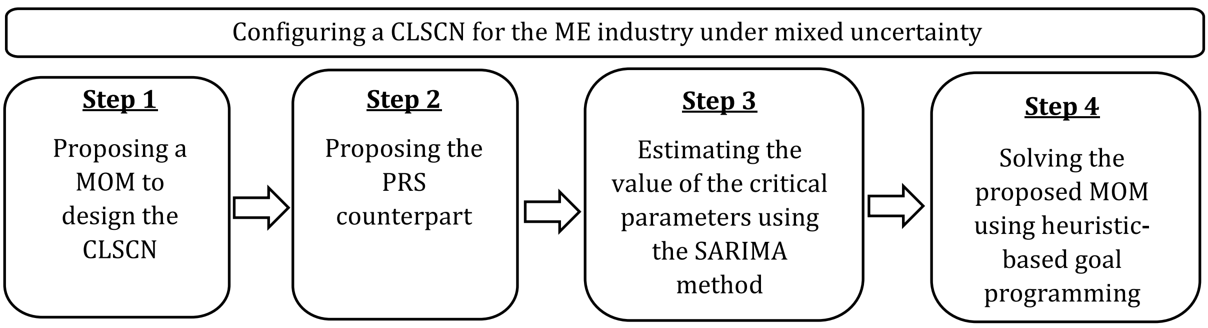

Fig. 1. The research framework

2. Literature Review

2.1. Related works

Some articles have considered some of the aforementioned paradigms separately and in combination; For example, (Nayeri et al. 2020) presented a sustainable CLSCN for a water reservoir. The goals considered in their problem model were optimization of financial, environmental, and social effects. In their designed problem, there were uncertainties such as customer demand and transportation costs, which the fuzzy robust model was applied to deal with them. The method of solving the problem is also ideal planning, the results of which show that the sustainable supply chain leads to the development of activities in several dimensions. Also, (Nayeri, Tavakoli, et al. 2021) suggested a robust stochastic-possibilistic model to design a responsive-resilient-sustainable SC To address uncertainty, an enhanced approach called fuzzy robust stochastic optimization (PRSO) was introduced. The model was applied in the water heater production industry, and the numerical results provided validation for the proposed model and the solution method that was developed. (Babaeinesami et al. 2021) configured a sustainable supply chain by incorporating both lean and agile factors simultaneously. The model took into account various aspects such as capacity and service level constraints, responsiveness, as well as sustainability measures. To solve the problem, they utilized a meta-heuristic multi-objective optimization algorithm called PMOPSO and compared its performance with the NSGA-II algorithm. (Fazli-Khalaf et al. 2021) focused on designing a sustainable SC for the tire industry, considering uncertain conditions. They incorporated resilience measures to enhance the reliability of the supply chain. The objectives of their study model included cost minimization, improved reliability, reduced carbon dioxide emissions, and increased social responsibilities. The findings of their study indicated that enhancing the resilience of the supply chain is beneficial for its sustainable development. (Sazvar, Tafakkori, et al. 2021) a capacity planning approach was presented to design a sustainable and resilient Supply Chain Network (SCN) under uncertain conditions. In their model, the influenza vaccine supply chain was designed, and the PRSO (Production, Recovery, Shipment, and Outsourcing) approach was employed to address uncertainty. To solve the model, multi-choice goal programming was utilized, and the results indicated that redundancy in the supply chain does not necessarily lead to an increase in total costs.. (Pahlevan et al. 2021) designed a sustainable SC in the aluminum industry. The main contribution of their study was the integration of sustainable security in Iran by using life cycle assessment (LCA) in environmental life and using two new meta-heuristic algorithms. Their results showed that the use of recycled materials in the production of recycled products has a great effect on reducing costs and also reducing carbon consumption.

(Asadi et al. 2022) suggested a robust model for a green and responsive CLSC for an air conditioner. In their study, the important reason was the production of the ventilator in the era of COVID-19. They used new methods to deal with the uncertainty of optimization. (Tavana et al. 2022) proposed a comprehensive framework for designing a sustainable SC. In their study, they introduced a multi-objective mixed integer linear programming (MOMILP) model to address supplier selection, order allocation, and transportation decisions. The fuzzy planning approach was employed achieve optimal solution. The outputs showed that enhancing the stability of the supply chain leads to improved overall performance of the chain. (Nayeri et al. 2022) presented a globally responsive SC considering sustainability and resilience paradigms. They stated that today according to the requirements of international businesses, it is important to pay attention to the characteristics of sustainability, resilience, responsiveness, and globalization. Therefore, in their paper, a mathematical model was presented in which the objectives were environmental impacts and total costs minimizing and social impacts maximizing based on the resilience and responsiveness dimensions. Also, the fuzzy stochastic robust approach had been used to deal with uncertainty. Their research solution method was also a new approach, augmented lexicographic weighted Tchebycheff method. The results of their study indicated that rising the level of supply chain responsiveness leads to increased job opportunities, safety, carbon emissions, and economic aspects. (Seydanlou et al. 2022) presented a sustainable CLSCN. In their study, they stated that Iran, as a developing country, should consider closed-loop policies for the design of SCNs so that it can receive the maximum output by considering sustainability criteria. In this regard, the model of their article considered a decision-making structure for location, allocation and inventory, which is designed with the multiple objectives of minimizing the total cost and reducing carbon dioxide emissions and increasing job opportunities. To solve the problem, a new meta-heuristic algorithm is proposed for the first time in the form of a combination of virus colony search (VCS) and refrigeration simulation (SA) and a combination of pseudo-electromagnetic algorithm (EMA) and genetic algorithm (GA). Their findings showed that this supply chain network in Iran's olive industry can lead to efficiency development. (Alinezhad et al. 2022) proposed a fuzzy model for the design of a sustainable CLSCN in the food industry. Their proposed network was a multi-product and multi-period problem that considered the fuzzy rate of return and demand. In order to deal with the uncertainty and solve the model, LP-Metric method and fuzzy linear programming have been used. Their findings showed that manufacturing outsourcing is highly recommended as an efficient solution during periods of high demand. (Arabi and Gholamian n.d.) designed a resilient CLSCN considering quality uncertainty in the mining industry. Their paper proposed a multi-period, multi-product mixed integer quadratic programming problem that considers resilience in mineral supply chains for the first time. Their results showed that transportation costs affect profit more than operating costs. (Ghalandari et al. 2023) presented a robust optimization hybrid model for designing a sustainable closed-loop supply chain network in the lead-acid battery industry. Their presented model had two-stage, in the first stage, candidate sites for recycling were evaluated using data envelopment analysis (DEA). They also considered geographical and technical criteria along with sustainability components in the evaluation. Their results showed that out of 23 candidate locations, 11 locations are suitable for creating a budget recycling location that was presented in the second stage of the proposed mathematical model. Their findings showed that with the implementation of such a model, the amount of carbon consumption will be reduced and it will also lead to cost optimization in the long run. (Abbasi et al. 2023) presented a new green closed loop supply chain network in Iran's automotive industry in the context of the Corona virus epidemic. In the proposed model, trade-offs between environmental and economic aspects are considered, and it helps to develop health issues in the supply chain by considering the health guidelines in the outbreak of the Corona epidemic. Their model was very sensitive to the cost structure and their main priority is cost minimization. Their proposed problem was solved using optimal programming and their findings showed that the proposed supply chain network became greener during the COVID-19 pandemic, but the total costs of the network increased during the epidemic. It has also had positive effects on greenhouse gas emissions and air quality during this period.

(Lee et al. 2024) presented an e-commerce supply chain network utilizing a demand-driven warehousing system under conditions of uncertainty. Their problem was solved using stochastic linear programming, and a stochastic approach was employed to cope with uncertainty. The results of their model demonstrate that the demand-driven warehousing system can significantly reduce supply chain costs under uncertain conditions. (Gao et al. 2024) designed a dual-channel closed-loop supply chain considering uncertain demand under conditions of uncertainty. They estimated demand using data-driven approaches and then solved the model using Mixed Integer Linear Programming (MILP). Their results indicated that the robust data-driven optimization approach can significantly enhance the performance of the supply chain network. In general, the summary of the literature review is shown in Table 1.

Table 1
Classifying the reported papers

Author	Supply chain			Uncertainty approach	Method	Case study
	Sustainability	Responsiveness	Closed loop			
(Nayeri et al, 2020)	*		*	FRO	Goal programming	Water reservoir
(Nayeri et al, 2021)	*	*		PRS	Goal programming	Water heater industry
(Babaeinesami et al, 2021)				---	Particle swarm optimization meta-heuristic algorithm (PMOPSO)	---
(Fazli-Khalaf et al, 2021)	*		*	---	A new mixed fuzzy possibilistic flexible programming method	Tire industry
(Sazvar et al, 2021)	*			Fuzzy robust optimization	goal programming with multiple objectives	Influenza vaccine
(Tavana et al, 2021)	*		*	---	Fuzzy goal programming	---
(Boronoos et al, 2021)			*	Robust optimization	Stochastic and flexible planning	Copier industry
(Pahlevan et al, 2021)	*		*	---	Multi-objective gray wolf optimizer (MOGWO)	Aluminum industry
(Asadi et al, 2022)	*			Robust optimization	multi-objective robust possibilistic programming model	Ventilator device
(Nayeri et al, 2022)	*	*		PRS	lexicographic weighted Tchebycheff method	Medical industry
(Seydanlou et al, 2022)	*		*	---	New meta-heuristic algorithm	Olive industry
(Alinezhad et al, 2022)	*		*	Fuzzy linear programming	Lp-metrics	Food industry
(Arabi & Gholamian, 2023)			*	Sensitivity analysis	Stochastic goal programming	Stone mining industry
(Abbasi et al, 2023)	*		*	---	Goal programming	Automotive industry
(Ghalandari et al, 2023)	*		*	Robust optimization	DEA	lead-acid battery industry

Author	Supply chain			Uncertainty approach	Method	Case study
	Sustainability	Responsiveness	Closed loop			
(Lee et al, 2024)		*		Stochastic optimization	MILP	E-commerce
(Gao et al, 2024)			*	Data driven robust	MILP	---
The current research	*	*	*	DDPRS	Heuristic-based meta goal programming	Medical equipment

The literature review reveals that while substantial progress has been made in designing sustainable and resilient supply chains, significant gaps remain unaddressed, particularly in integrating sustainability and resilience under mixed uncertainty within CLSCN frameworks. Most studies have focused either on addressing sustainability or resilience individually, often neglecting the importance of a data-driven approach to manage uncertainties, which is essential in today's complex and competitive environment. Additionally, few studies incorporate a comprehensive, multi-objective approach that balances sustainability and responsiveness metrics in the context of real-world industries. This research aims to bridge these gaps by introducing a data-driven model that simultaneously optimizes sustainability and responsiveness under mixed uncertainties, thereby contributing a novel framework that is both innovative and practically applicable.

2.2. Contribution statement

As aforementioned, in recent times, the crucial role of the supply chains attracted the managers and researchers focus for the optimal configuring of SCs. In this regard, although many articles were published in this area, there are still various gaps that should be covered. For example, as can be seen in Table 1, despite conducting several articles in the field of the CLSCN, the simultaneous incorporation of sustainability and resiliency into the CLSCN, especially under mixed uncertainty, has been rarely discussed in the literature. However, as stated in the introduction, both of these concepts are vital for improving the efficiency and performance of supply chains. Interestingly, the literature reveals that the utilization of data-driven approaches to address uncertainty has been relatively neglected by researchers. However, in the nowadays complex, competitive, and dynamic marketplace, uncertain situation is an issue that managers should pay attention, and employing efficient approaches to tackle uncertainty is so important. For this purpose, developing data-driven approaches that can significantly deal with the high level of uncertainty may be a helpful tool. Given the significance of the aforementioned points, this study seeks to address the identified gaps by developing a data-driven model for configuring a CLSCN, with a focus on two critical aspects: responsiveness and sustainability, under conditions of mixed uncertainty in the ME industry. To achieve this, a multi-objective model (MOM) is proposed that optimizes sustainability metrics while taking into account responsiveness factors. Following this, a data-driven Probabilistic Risk Simulation (PRS) method is developed to handle mixed uncertainty. Subsequently, a heuristic-based Multi-Choice Goal Programming (MGP) approach is designed to solve the research problem. In summary, the key contribution of this work is the introduction of a comprehensive data-driven decision-making framework for designing a responsive and sustainable CLSCN tailored to the needs of the ME industry.

This section is divided into four main parts as follows: (i) defining the research problem and proposing the MOM, (ii) dealing with mixed uncertainty using the PRS method, (iii) defining the SARIMA method, and (iv) defining the heuristic-based goal programming method.

3.1. Problem definition

This article studies the Sustainable and Responsive CLSCN (SRCLSCN) problem. For this purpose, the considered network has three facilities in the forward chain namely Production Centers (PCs), Distribution Centers (DCs), and customers. Furthermore, this network includes three facilities in the reverse chain namely Collection Centers (CCs), Repairing Centers (RCs), and disposal centers (See Figure 2). In this research, two different types of products are considered. The first type is the New Products (NPs) manufactured in the PCs, and the second type is the Repaired Products (RPs) that are obtained by repairing the returned products in the RCs. It should be noted that the repaired products have less quality but have less price. In this network, the new products are transferred from the PCs to the DCs and before demand points delivery. Then, the EOU (End-of-Use) and EOL (End-of-Life) products are collected by the CCs. In the RCs the percentage of products that are successfully repaired are sent to the DCs to ship to the market and others are sent to disposal centers. Note that PCs and RCs can be established utilizing different technologies and each technology has its characteristics (setup cost, operating cost, and emissions). Also, in this research, different Transportation Modes (TMs) are considered, and products can be sent by different vehicles, which have different costs, capacities, and emissions. Also, this research considers a service level for the supply chain. According to the service level, the ratio of the satisfied demand over the overall demand must be bigger than a predefined value

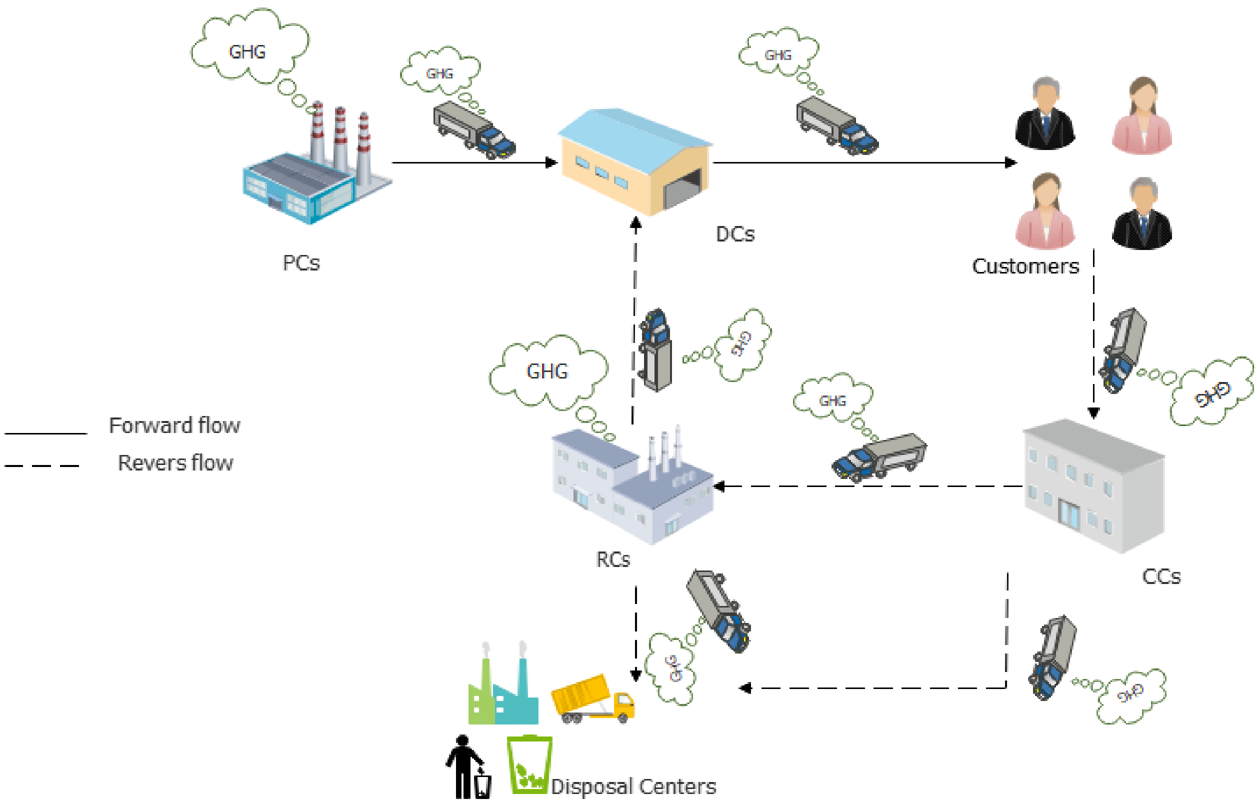

Fig. 2. The designed network

In the following, the notations of the proposed MOM are presented.

Indices

i	Index of production centers
j	Index of distribution centers
k	Index of customers
c	Index of collection centers
r	Index of repairing centers
d	Index of disposal centers
n	Index of NPs
u	Index of RPs
q	Index of TMs
t	Index of technologies
s	Index of scenarios

Parameters

$\widetilde{fom}_{it}$	The Establishment Cost (EC) for production center i with technology t
$\widetilde{fod}_{j}$	The EC for distribution center j
$\widetilde{foc}_{c}$	The EC for collection center c
$\widetilde{for}_{rt}$	The RC for repairing center r with technology t
$Mcap_{it}$	The capacity of PC i with technology t
$Rcap_{rt}$	The capacity of RC r with technology t
$Ccap_{c}$	The capacity of CC c
$Dcap_{j}$	The capacity of DC j
$\widetilde{dn}_{kns}$	The demand kth customer for NP n Under Scenario s (US)

$\widetilde{du}_{kus}$	The demand kth customer k for RP u US s
$\widetilde{hp}_{int}$	The manufacturing cost in PC i with technology t
$\widetilde{hd}_{j}$	The operation cost in DC j
$\widetilde{hc}_{cn}$	The collection cost for NP n in CC c
$\widetilde{hr}_{rnt}$	The repairing cost in RP r with technology t
$\widetilde{SC}_{kn}$	The shortage cost for NP n for customer k
$\widetilde{SCU}_{ku}$	The shortage cost for RP u for customer k
$\widetilde{TC}_{q}$	The transportation cost for TM q
$d1_{ij}$	Distance Between Nodes (DBN) i and j
$d2_{jk}$	DBN j and k
$d3_{kc}$	DBN k and c
$d4_{cr}$	DBN c and r
$d5_{cd}$	DBN c and d
$d6_{rj}$	DBN r and j
$d7_{rd}$	DBN r and d
α_{ns}	Rate of return for NP n under scenario s
β_{n}	The percentage of repairable product for NP n
θ	The rate of successful repair
$\widetilde{\lambda m}_{it}$	The amount of emissions in production process with technology t
$\widetilde{\lambda R}_{rt}$	The amount of emissions in the repairing process with technology t
$\widetilde{\lambda T}_{q}^{t}$	The amount of emissions in transporting process with TM q
$\widetilde{NJM}_{it}$	The number of jobs created by establishing PC i with technology t
$\widetilde{NJD}_{j}$	The number of jobs created by establishing DC j
$\widetilde{NJC}_{c}$	The number of jobs created by establishing CC c
$\widetilde{NJR}_{it}$	The number of jobs created by establishing RC r with technology t
SL	The service level of the SC

Decision Variables

QMD_{ijnt}^{qs}	The quantity of NP n sent from ith PC to jth DC by TM q US s
QDD_{jkn}^{qs}	The quantity of NP n sent from jth DC to kth customer by TM q US s
$QUDD_{jku}^{qs}$	The quantity of RP u sent from jth DC to kth customer by TM q US s
QDC_{kcn}^{qs}	The quantity of NP n shipped from kth customer to cth CC by TM q US s
QCR_{crnt}^{qs}	The quantity of NP n shipped from cth CC to rth RC by TM q US s
QCD_{cdn}^{qs}	The quantity of NP n shipped from cth CC to dth disposal center by TM q US s
QRD_{rjut}^{qs}	The quantity of RP u shipped from rth RC to jth DC by TM q US s
rem_{rnts}	The total repaired products US s
QDR_{rd}^{qs}	The amount of products sent from rth RC to dth disposal center by TM q US s
SN_{kn}^{s}	The amount of shortage for NP n in demand point k US s
SU_{ku}^{s}	The amount of shortage for RP u in demand point k US s
YM_{it}	A binary variable that equals 1 if PC i with technology t is opened
YD_{j}	A binary variable that equals 1 if DC j is opened
YC_{c}	A binary variable that equals 1 if CC c is opened
YR_{rt}	A binary variable that equals 1 if RC r with technology t is opened
X_{ijq}	A binary variable that equals 1 if TM q is utilized between facilities i and j

X_{jkq}	A binary variable that equals 1 if TM q is utilized between facilities j and k
X_{kcq}	A binary variable that equals 1 if TM q is utilized between facilities k and c
X_{crq}	A binary variable that equals 1 if TM q is utilized between facilities c and r
X_{cdq}	A binary variable that equals 1 if TM q is utilized between facilities c and d
X_{rjq}	A binary variable that equals 1 if TM q is utilized between facilities j and q
X_{rdq}	A binary variable that equals 1 if TM q is utilized between facilities d and q

In the following, the proposed MOM is presented.

Equation (1) is the first OF. This OF aims at minimizing the overall costs of the SC.

$$\begin{aligned}Min\ Z_1 = {} & \sum_{i,t} \widetilde{fom}_{it}.YM_{it} + \sum_{j} \widetilde{fod}_j.YD_j. + \sum_{c} \widetilde{foc}_c.YC_c + \sum_{r}\sum_{t} \widetilde{for}_{rt}.YR_{rt} \\ & + \sum_{s} Ps_s.\left(\sum_{i,j,t,n,q} \widetilde{hp}_{int}.QMD_{ijnt}^{qs} + \sum_{j,k,t,q,n,u} \widetilde{hd}_j.(QDD_{jkn}^{qs} + QUDD_{jku}^{qs}) \right. \\ & + \sum_{c,r,n,t,r} \widetilde{hc}_{cn}.(QCR_{crnt}^{q} + QCD_{cbn}^{qs}) + \sum_{r,n,t} \widetilde{hr}_{rnt}.rem_{rnts} + \sum_{k,n} \widetilde{SC}_{kn}.SN_{kn}^{s} + \sum_{k,u} \widetilde{SCU}_{ku}.SU_{ku}^{s} \\ & + \sum_{q} \widetilde{TC}_q.\left(\sum_{i,j,n,t} d1_{ij}.QMD_{ijnt}^{qs} + \sum_{j,k,n} d2_{jk}.QDD_{jkn}^{qs} + \sum_{j,k,u} d2_{jk}.QUDD_{jku}^{qs} + \sum_{k,c,n} d3_{kc}.QDC_{kcn}^{qs} \right. \\ & \left.\left. + \sum_{c,r,n} d4_{cr}.QCR_{crnt}^{qs} + \sum_{c,d,n} d5_{cd}.QCD_{cdn}^{qs} + \sum_{r,j,u,t} d6_{rj}.QRD_{rjut}^{qs} + \sum_{r,d} d7_{rd}.QDR_{rd}^{qs} \right)\right)\end{aligned} \tag{1}$$

The second OF shown in Equation (2) attempts to minimize the environmental impacts.

$$\begin{aligned}Min\ Z_2 = {} & \sum_{s} Ps_s.\left(\sum_{q,n,j,i,t} \widetilde{\lambda m}_t.QMD_{ijnt}^{qs} + \sum_{r,n,t} \widetilde{\lambda R}_{rt}.rem_{rnts} \right. \\ & + \left(\sum_{q} \widetilde{\lambda T}_q .\left(\sum_{i,j,n,t} d1_{ij}.QMD_{ijnt}^{qs} + \sum_{j,k,n} d2_{jk}.QDD_{jkn}^{qs} + \sum_{j,k,u} d2_{jk}.QUDD_{jku}^{qs} \right.\right. \\ & + \sum_{k,c,n} d3_{kc}.QDC_{kcn}^{qs} + \sum_{c,r,n} d4_{cr}.QCR_{crnt}^{qs} + \sum_{c,d,n} d5_{cd}.QCD_{cdn}^{qs} + \sum_{r,j,u,t} d6_{rj}.QRD_{rjut}^{qs} \\ & \left.\left.\left. + \sum_{r,d} d7_{rd}.QDR_{rd}^{qs} \right)\right)\right)\end{aligned} \tag{2}$$

On the other hand, the third OF shown in Relation (3) maximizes the social impacts.

$$Max\ Z_3 = \sum_{i,t} \widetilde{NJM}_{it}.YM_{it} + \sum_{j} \widetilde{NJD}_j.YD_j. + \sum_{c} \widetilde{NJC}_c.YC_c + \sum_{r}\sum_{t} \widetilde{NJR}_{rt}.YR_{rt} \tag{3}$$

Relations (4)-(7) represent the capacity limitations in the model. Equation (4) represents the limitation on capacity for the production centers (PCs), Equation (5) represents the limitation on capacity for the distribution centers (DCs), Relation (6) represents the capacity constraint for the collection centers (CCs), and Equation (7) represents the capacity constraint for the recycling centers (RCs). Additionally, constraints (8) and (9) specify that the PCs and RCs can only be established using a single technology.

$$\sum_{j,q} QMD_{ijnt}^{qs} \leq Mcap_i . YM_{it} \qquad \forall_{i,n,t,s} \qquad (4)$$

$$\sum_{q,i} QMD_{ijn}^{qs} + \sum_{q,r,t} QRD_{rjut}^{qs} \leq Dcap_j . YD_j \qquad \forall_{j,n,u,s} \qquad (5)$$

$$\sum_{q,r,t} QCR_{crnt}^{qs} + \sum_{q,d} QCD_{cdn}^{qs} \leq Ccap_c . YC_c \qquad \forall_{c,r,n,s} \qquad (6)$$

$$\sum_{j,q} QRD_{rjut}^{q} \leq Rcap_{rt} . YR_{rt} \qquad \forall_{r,u,t} \qquad (7)$$

$$\sum_{t} YM_{it} \leq 1 \qquad \forall_{i} \qquad (8)$$

$$\sum_{t} YR_{rt} \leq 1 \qquad \forall_{r} \qquad (9)$$

On the other hand, relations (10) to (14) are the flow balance constraints. In this context, constraint (10) calculates the amount of product sent from DCs to customers and also the number of shortages of the NPs in the demand points. Equation (11) calculates the amount of repair product sent to demand points. Equation (12) is the flow balance constraint between the PCs and DCs. Constraint (13) calculates the amounts of repaired products. Equation (14) is the flow balance constraint between the demand points and CCs. Constraint (15) determines the quantity of products transported from collection centers to repair centers. Equation (16) computes the quantity of products transported from collection centers to disposal centers. Constraints (17) and (18) calculate the total amount of repaired products. Constraint (19) computes the amount of product transmitted from the RCs to the disposal center.

$$\sum_{q,j} QDD_{jkn}^{qs} + SN_{kn}^{s} \geq \widetilde{dn}_{kns} \qquad \forall_{k,n,s} \qquad (10)$$

$$\sum_{q,j} QUDD_{jku}^{qs} + SU_{ku}^{s} \geq \widetilde{du}_{kus} \qquad \forall_{k,u,s} \qquad (11)$$

$$\sum_{q,i} QMD_{ijn}^{qs} = \sum_{q,k} QDD_{jkn}^{qs} \qquad \forall_{j,n,s} \qquad (12)$$

$$\sum_{q,r,t} QRD_{rjut}^{qs} = \sum_{q,k} QUDD_{jku}^{qs} \qquad \forall_{j,u,s} \qquad (13)$$

$$\alpha_n . \sum_{q,j} QDD_{jkn}^{qs} = \sum_{c,q} QDC_{kcn}^{qs} \qquad \forall_{k,n,s} \qquad (14)$$

$$\beta_n . \sum_{q,k} QDC_{kcn}^{qs} = \sum_{q,r,t} QCR_{crnt}^{qs} \qquad \forall_{c,n,s} \qquad (15)$$

$$(1-\beta_n) . \sum_{q,k} QDC_{kcn}^{qs} = \sum_{q,d} QCD_{cdn}^{qs} \qquad \forall_{c,n,s} \qquad (16)$$

$$rem_{rnts} = \theta . \sum_{q,c} QCR_{crnt}^{qs} \qquad \forall_{r,n,t,s} \qquad (17)$$

$$\sum_{q,c} QRD_{rjut}^{qs} = rem_{rnts} \qquad \forall_{r,n,u,t,s} \qquad (18)$$

$$\sum_{q,d} QDR_{rd}^{qs} = (1-\theta).\sum_{q,c,n} QCR_{crnt}^{qs} \qquad \forall_{s,r} \qquad (19)$$

In the following, transport constraints between supply chain nodes are presented. In this regard, constraints (20)-(29) state that a transportation mode can be utilized between two facilities only if those facilities have been established.

$$X_{ijq} \leq \sum_{t} YM_{it} \qquad \forall_{i,q} \qquad (20)$$

$$X_{ijq} \leq YD_j \qquad \forall_{i,j,q} \qquad (21)$$

$$X_{jkq} \leq YD_j \qquad \forall_{j,k,q} \qquad (22)$$

$$X_{kcq} \leq YC_c \qquad \forall_{k,c,q} \qquad (23)$$

$$X_{cdq} \leq YC_c \qquad \forall_{c,d,q} \qquad (24)$$

$$X_{crq} \leq YC_c \qquad (25)$$

$$X_{crq} \leq \sum_{t} YR_{rt} \qquad \forall_{c,r,q} \qquad (26)$$

$$X_{rjq} \leq YD_j \qquad \forall_{r,j,q} \qquad (27)$$

$$X_{rjq} \leq \sum_{t} Y_{rt} \qquad \forall_{r,j,q} \qquad (28)$$

$$X_{rdq} \leq \sum_{t} Y_{rt} \qquad \forall_{r,d,q} \qquad (29)$$

Eventually, Relation (30) is the service level constraint. The service level is calculated based on the satisfied demand and potential demand.

$$\frac{\sum_{s,q,j,k,n} QDD_{jkn}^{qs}}{\sum_{k,n,s} \widetilde{dn}_{kns}} \geq SL \qquad (30)$$

3.2. Data-driven PRS to tackle mixed uncertainty

3.2.1 Fuzzy robust stochastic optimization

As aforementioned, uncertainty is a major challenge in SCND problems. In general, the uncertainty can be classified according to Table 2. On the other hand, different methods to tackle uncertainty can be categorized according to Figure 3. This research, owing to the high level of uncertainty in the SCM problem, especially after the COVID-19 pandemic, investigates the considered problem under the mixed uncertainty. In this type, both epistemic and randomness uncertainties are considered as the fuzzy-scenario parameters. To tackle this type of uncertainty, the current study selects the fuzzy robust stochastic method that is a widely-employed approach in the literature and showed appropriate performance (see (Gholizadeh et al. 2020; Mamashli, Nayeri, et al. 2021; Nasrollah et al. 2022; Nayeri, Tavakoli, et al. 2021; Nayeri, Torabi, et al. 2021)).

Table 2
Diverse noun of uncertainty (Mamashli, Nayeri, et al. 2021)

Type	Description
Randomness	The historical data at hand can be utilized to calculate the likelihood distribution, yet it's important to acknowledge that the parameter in question inherently possesses a random characteristic.
Epistemic	Based on the limited information in the input data, it is necessary to gather additional data from experts in order to estimate the probability distribution accurately. The input data alone may not provide sufficient information, and expert input is valuable in determining the probability distribution.

Deep uncertainty	Due to the lack of information in the input data, it is challenging to accurately estimate the possibility or probability of plausible future conditions. Without sufficient information, it becomes difficult to assess the likelihood of different scenarios or outcomes. Additional data or insights are needed to make more informed estimations about the possibilities and probabilities of future conditions.

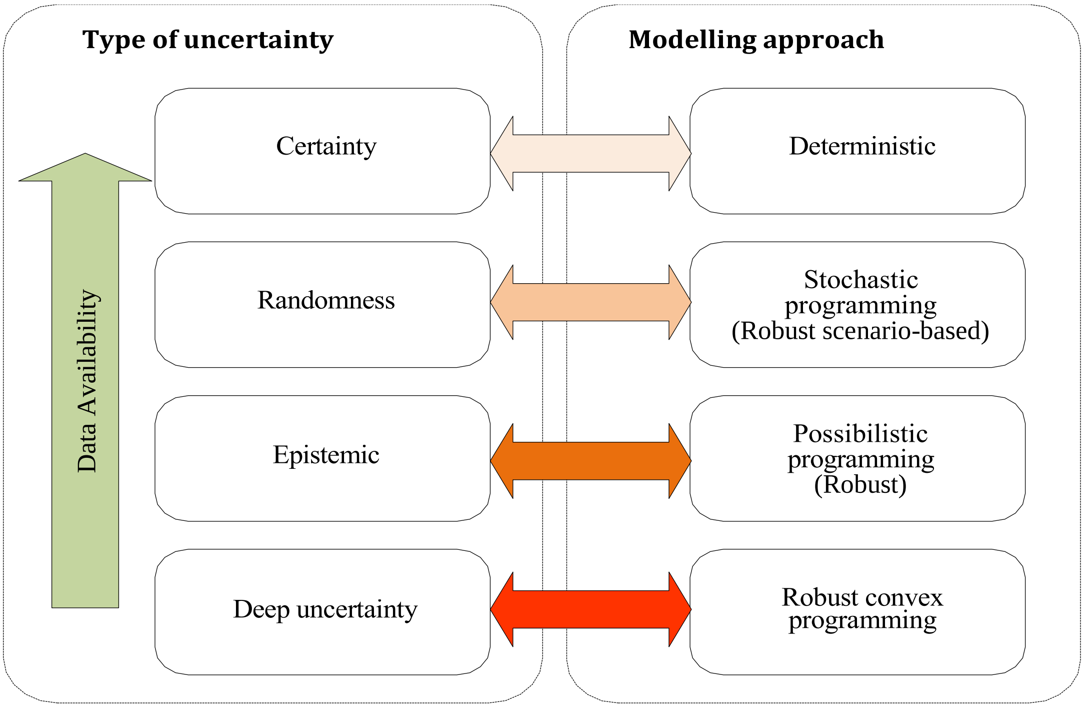

Fig. 3. The approaches that used to tackle uncertainty (Bairamzadeh et al. 2018)

In the following, we have briefly described the PRS method. Let f, c, and d are triangular fuzzy parameters and A, h and L denote coefficients of constraint. In addition, x is the design variable and y_s represents the controlling variable. Finally, p_s is the probability of each scenario. Now, consider model (3)

$$\begin{aligned}
&\text{Min } Z = \tilde{g}.x + \sum_s p_s.\tilde{u}.y_s \\
&Ax \le \tilde{d} \\
&Ly_s \ge \tilde{h}_s \\
&x, y_s \ge 0
\end{aligned} \tag{31}$$

the PRS counterpart for the above model can be written as follows (Fazli-Khalaf et al. 2017) where β shows the optimality robustness' weight, δ denotes the feasibility robustness' weight, and τ and ϑ represent the constraints' satisfaction levels.

$$\begin{aligned}
&\text{Min } Z = \left[\frac{g^1+g^2+g^3}{3}\right].x + \sum_s p_s.\left[\frac{u^1+u^2+u^3}{3}\right].y_s \\
&\qquad + \beta \sum_s p_s.\left[\left(\left[\frac{u^1+u^2+u^3}{3}\right].y_s - \sum_{s'} p_{s'}.\left[\frac{u^1+u^2+u^3}{3}\right].y_{s'}\right) + 2\theta_s\right] + \sum_s \varphi.\psi_s \\
&Ax \le (2\tau-1).d^1 + (2-2\tau).d^2 \\
&Ly_s + \psi_s \ge (2-2\vartheta).h_s{}^3 + (2\vartheta-1).h_s{}^2 \\
&\left[\frac{f^1+f^2+f^3}{3}\right].y_s - \sum_s p_s.\left[\frac{f^1+f^2+f^3}{3}\right].y_s + \theta_s \ge 0
\end{aligned} \tag{32}$$

3.2.2 The SARIMA method

To handle the uncertainty related to the demand parameters and the product return rate corresponding to each of the two products of the oxygen generator and the blood refrigerator, a stochastic data-driven optimization approach has been used. The approach is that the amount of demand and the return rate of the product in each scenario are estimated according to the available data. The advantage of this method over other approaches is the more accurate findings and the estimated parameter value (Bertsimas et al. 2018; Boroun et al. 2023). In this regard, three optimistic, probable, and pessimistic scenarios have been defined to predict the demand and the return rate of model products. The data corresponding to each scenario is selected separately and based on it, the desired parameters are estimated using the SARIMA approach. Since the amount of demand is also fuzzy, in each scenario, the amount of demand is estimated in a fuzzy way. Therefore, the SARIMA algorithm is used to predict the demand parameter, and the output of each prediction corresponds to the values of the optimistic scenario(θ1), probable scenario (θ2), and pessimistic scenario (θ3) for demand. The reason for using SARIMA algorithm is higher accuracy in estimating parameters based on seasonal data (Tavakoli et al. 2022, 2023).

In order to optimize the performance of time series forecasting algorithms, several parameters need to be adjusted that explained below.

Trend elements:

- pTrend: The automatic regression order determines the number of lagged terms included in the autoregressive (AR) component of the SARIMA model.
- dTrend: The difference order refers to the number of times the time series data is differenced to achieve stationarity in the SARIMA model.
- qTrend: The moving average order specifies the number of past error terms included in the moving average (MA) component of the SARIMA model, which is used to capture the residual patterns in the time series data.

Seasonal elements:

- Seasonal self-recovery order: Determines the number of lagged terms included in the seasonal autoregressive (SAR) component of the SARIMA model.
- Seasonal difference order: Specifies the number of times the seasonal component of the time series data is differenced to achieve stationarity in the SARIMA model.
- Quarterly moving average order (Q): Represents the number of past error terms included in the seasonal moving average (SMA) component of the SARIMA model, which captures the residual patterns at the seasonal level.
- m: Refers to the number of time steps within a single seasonal period, defining the seasonal pattern of the time series data.

In order to achieve predictions, the SARIMA(p, d, q)(P, D, Q)m parameters need to be optimized. To achieve this, the "grid search" approach is employed, which involves systematically exploring different permutations of these hyperparameters. During the search process, the Akaike Information Criterion (AIC) value serves as the primary measure for evaluation. The goal is to select the SARIMA model with the lowest AIC value, indicating the best fit to the data. AIC measures the goodness of fit of a model to the data while considering the model's overall complexity. It provides a balance between the model's fit to the data and its complexity by penalizing overly complex models (Alizadeh et al. 2022; Rahmanian et al. 2021).

3.4. Solution approach

Given that the model presented is a multi-objective issue, a Multiple-Objective Decision-Making (MODM) approach is employed in this research. Furthermore, the supply chain configuration problem is classified as an Np-Hard problem (Nasrollah et al. 2022). So, this study is used a heuristic algorithm and the MGP method. In the following, the mentioned methods are defined.

3.4.1. Meta-Goal Programming (MGP)

Goal Programming (GP) is a well-known approach in the literature that is widely used to solve multi-objective models (Nayeri et al. 2018). Various adaptations of this method have been utilized in numerous studies in prior research, demonstrating satisfactory performance (see (Asadi et al. 2022; Jamali et al. 2021; Nayeri, Torabi, et al. 2021; Yadollahinia et al. 2018)). One of the efficient versions of GP is meta-GP (MGP) developed by Uría et al. (2002), which has several advantages, such as the capability of achieving more balanced solutions and the flexibility for modeling the decision-makers preferences (Asadi et al. 2022). Suppose that t_i shows the target value for objective function i, n_i and respectively are the negative and positive deviations. In this approach, three types of deviations are defined that their formulation are shown in relations (33)-(35).

- 1) The weighted sum of deviations should be less that a predefined value ($Q1$). In equation (33), δ_i demonstrates the weight of objective function i.

$$\sum_{i=1}^{q} \delta_i . \frac{p_i}{t_i} \leq Q_1 \tag{33}$$

- 2) The utmost deviation in percentage ought to remain under a predetermined threshold of (Q_2).

$$Max_{i=1..,q}\left\{\delta_i.\frac{p}{t_i}\right\}\leq Q_2 \qquad \begin{cases}\delta_i.\frac{p_i}{t_i}-D\leq 0 & i=1,\dots,q\\ D\leq Q_2\end{cases} \tag{34}$$

In relation (34), D is the maximum weighted percentage deviation.

- 3: The proportion of goals not met must not surpass a pre-established value of (Q_3). In relation (35), Gi is a binary variable and Mi is a large number.

$$p_i - M_i.y_i \leq 0, i=1,\dots,q$$
$$\frac{\sum_{i=1}^{q} G_i}{q}\leq Q_3 \tag{35}$$

The formulation of MGP is shown in Relation (36) which can be structured as either the weighted form or the MinMax form. It should be noted that this method was developed by Uría et al. (2002) and employed in several papers such as (Asadi et al. 2022; Nayeri, Torabi, et al. 2021).

$$\begin{aligned}
&Min\ (\beta_1,\beta_2,\beta_3)\\
&f_i(x)+n_i-p_i=t_i && i=1,\dots,q\\
&g_j(x)\leq b_j\\
&\sum_{i=1}^{q}\delta_i.\frac{p_i}{t_i}+\alpha_1-\beta_1=Q_1\\
&\delta_i.\frac{p_i}{t_i}-D\leq 0 && i=1,\dots,q\\
&D+\alpha_2-\beta_2=Q_2\\
&p_i-M_i.G_i\leq 0 && i=1,\dots,q\\
&\frac{\sum_{i=1}^{q}G_i}{q}+\alpha_3-\beta_3=Q_3\\
&x,n_i,p_i,\alpha_j,\beta_j\geq 0\quad G_i\in\{0,1\} && i=1,\dots,q\\
& && j=1,2,3
\end{aligned}\tag{36}$$

3.4.2. The heuristic algorithm

As mentioned, one of the major challenges of solving the proposed MOM is its complexity, which significantly increases the computational time. In this research, to decrease the solution time, we have employed a heuristic algorithm which is widely employed in the literature and shows acceptable performance (for instance see (Asadi et al. 2022; Gholizadeh et al. 2021; Kaur and Singh 2018; Mamashli, Bozorgi-Amiri, et al. 2021; Nayeri, Tavakkoli-Moghaddam, et al. 2021; Sazvar, Zokaee, et al. 2021)). The following outlines the procedural steps of the applied heuristic algorithm(Kaur and Singh 2018; Mamashli, Bozorgi-Amiri, et al. 2021):

Step 1) Relax the binary constraint. In other words, convert the binary variables (e.g., YD_j and X_{ijq}) to continuous variable.
Step 2) Solve the relaxed model.
Step 3) If the value of the relaxed variable is equal to 1, fixed it on this value. On the other hand, if the value of the relaxed variable is equal to zero, fixed it on this value. Otherwise, the relaxed variable remains variable.
Step 4): Solve the new problem.
Step 5): If all relaxed variables are equal to one or zero, the algorithm is finished, otherwise, go to Step 3.

4. Numerical Results

4.1. Case study

As mentioned, the current study chooses the ME industry as a real-world application to show the performance and efficiency of the proposed data-driven model. The COVID-19 outbreak has caused a lot of financial and human losses in the last three years. Amid the pandemic, the medical equipment industry has been notably instrumental in enhancing healthcare services. According to the report of the World Health Organization (WHO), one of the vital parts of healthcare systems is medical equipment, and its role in the health of society is undeniable. Therefore, given the high importance of the mentioned industry, the current research has chosen the ME industry as a case study. In this field, company ABC located in Mazandaran province, Iran, is selected as a case study. Since during the Coronavirus disease pandemic the demand for Oxygen concentrator (due to the significant need of patients for oxygen) and the demand for blood refrigerator (due to the increased need for blood) increased significantly, which shows the high importance and application of these products, this paper has selected these two products. Figure 4 shows these products. In this regard, Table 3 presents the size of the problem. On the other hand, Table 4 shows the value of some cost-related parameters. Also, this research considers three different transportation modes namely Heavy-duty truck, Mid-size truck, and Light truck, which their information is provided in Table 5. Other important parameters are estimated in Section 4.2. It is important to mention that two modes are taken into account for production and repair technologies. The first mode is characterized by lower setup costs but higher pollution levels, while the second mode has higher setup costs but lower pollution levels. In general, the relevant data was obtained from documented data provided by organization ABC. Demand data for different years was available, and based on the conditions stated for each year, optimistic, probable, and pessimistic scenarios were estimated. Other parameters were also gathered using data from organization ABC.

(a) Oxygen concentrator

(b) blood refrigerator

Fig. 4. The considered products

Table 3
The size of the problem

Facility	PC	DC	Customer	CC	RC	Disposal center
#Number	3	5	10	3	3	1

Table 4
The value of some fuzzy cost-related parameters

Parameter		Value θ_1	θ_2	θ_3
$\widetilde{fom}_{it}$ (Million Toman)		800	900	1000
$\widetilde{fod}_j$ (Million Toman)		200	300	400
$\widetilde{foc}_c$(Million Toman)		200	300	400
$\widetilde{for}_{rt}$ (Million Toman)		500	600	700
$\widetilde{SC}_{kn}$	$n = 1$	10	12	15
	$n = 2$	35	40	45
$\widetilde{hd}_j$) (Million Toman)		0.3	0.6	0.9

Table 5
Information about the transportation modes

Parameter	Mode	Light truck	Mid-size truck	Heavy duty truck
Cost (Toman/Kg-Km)	c^1	0.0115	0.120	0.125
	c^2	0.06575	0.122	0.127
	c^3	0.120	0.125	0.130
CO2 emission factor (Kg/ton-Km)	c^1	0.01	0.03	0.04
	c^2	0.02	0.04	0.05
	c^3	0.03	0.05	0.06

4.2. The outputs of the SARIMA method

As mentioned before, the approach used to deal with demand uncertainty is fuzzy stochastic data-driven optimization. In this regard, three scenarios have been defined, according to each of the scenarios, the demand is estimated in a fuzzy environment using historical data.

4.2.1 Product demand forecasting

In this section, the demand for products in each of the scenarios is described separately.

• The optimistic scenario in this study occurs when the demand for products decreases, which happens when the overall health status of the community is at an appropriate level. During the years 2013 to 2015 in Iran, with the implementation of healthcare reform policies, the rate of medical visits has decreased, leading to a reduction in the use of refrigerators and oxygen generators. Therefore, based on the data from those years, the demand for the optimistic scenario has been estimated, which is shown in Figure 5.

Fig. 5. Forecasting product demand in the optimistic scenario

• In the probable scenario, the utilization of medical equipment is balanced due to the usual state of the community. In Iran, prior to the COVID-19 era, this scenario occurred during the time period of 2017 to 2019. Therefore, historical data from 2017 to 2019 have been utilized to estimate the demand parameters in the probable scenario, which is shown in Figure 6.

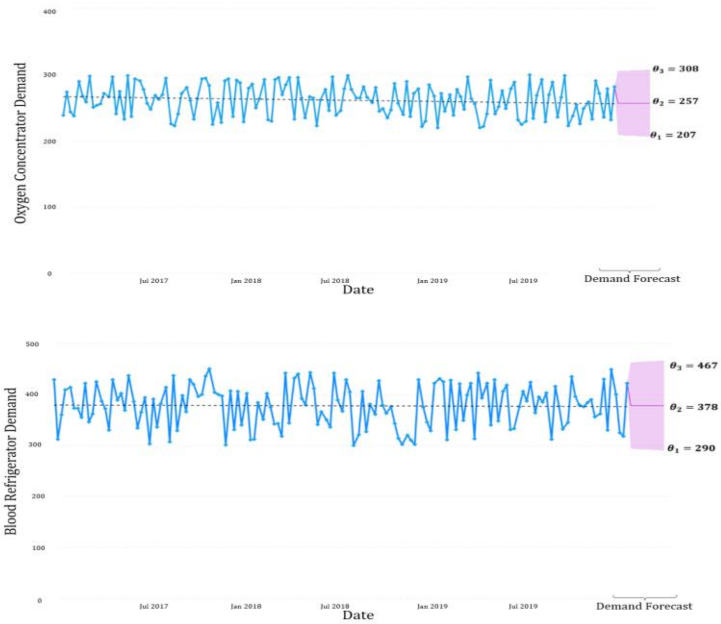

Fig. 6. Forecasting product demand in the probable scenario

• The pessimistic scenario represents a situation where COVID-19 has spread globally, resulting in the highest demand for blood storage refrigerators and oxygen generators. In this scenario, data from the years 2020 to 2022 has been used. During this time period, the utilization of medical equipment and oxygen generators significantly increased due to the spread of the coronavirus.

Fig. 7. Forecasting product demand in the pessimistic scenario

According to the analysis depicted in Table 6 the estimated values for the demand of the products according to each scenario are shown**.**

Table 6
Amount of demand in different scenarios for two products

Scenario	**Demand**		
	θ_1	θ_2	θ_3
Oxygen generator			
Optimistic scenario	92	141	190
Probable scenario	207	257	308
Pessimistic scenario	380	489	598
Blood storage refrigerator			
Optimistic scenario	185	237	290
Probable scenario	290	378	467
Pessimistic scenario	593	702	810

4.2.2 Product in need of repair demand forecasting

Product in need of repair demand also has uncertainty like the product demand, which is estimated based on past data and SARIMA algorithm like the original demand. The figure 8 shows the demand forecast for repair products in the optimistic scenario, figure 9 shows the demand forecast for repair products in the probable scenario and figure 10 shows the demand forecast for repair products in the pessimistic scenario.

- Optimistic scenario

Fig. 8. Forecasting product in need of repair demand in the optimistic scenario

- Probable scenario

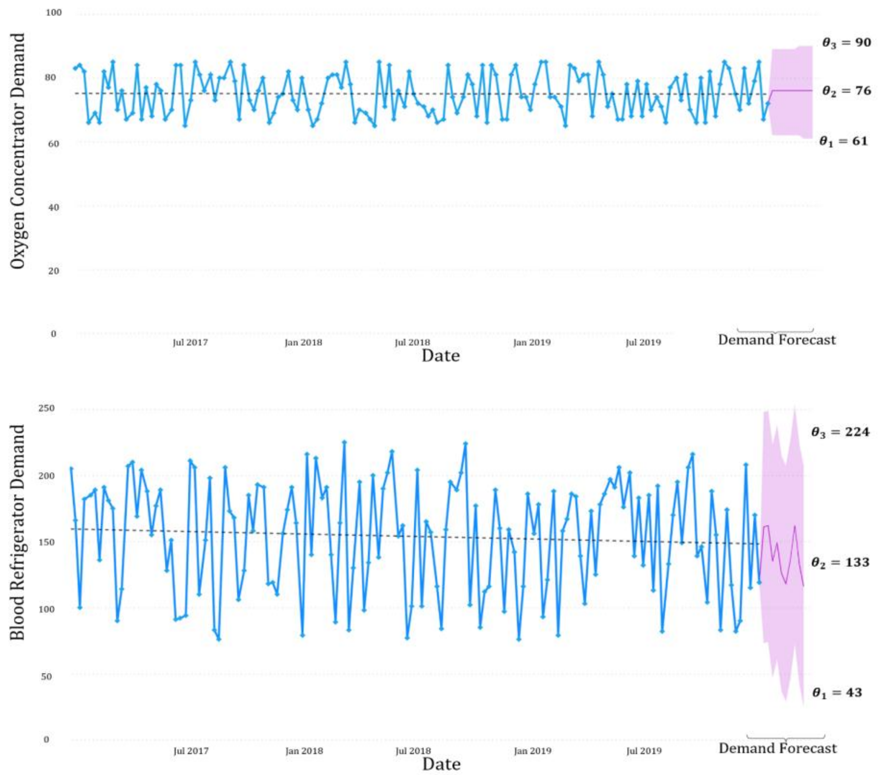

Fig. 9. Forecasting product in need of repair demand in the probable scenario

- Pessimistic scenario

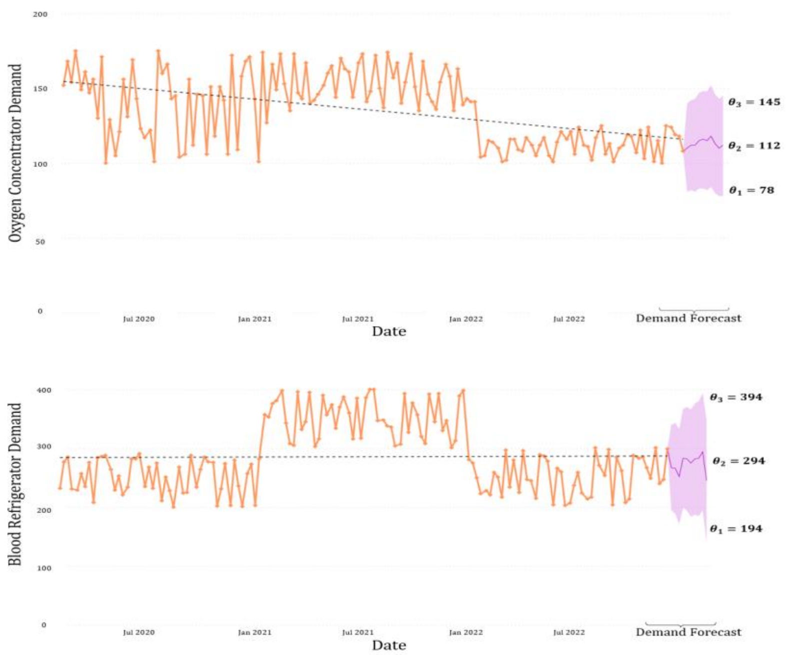

Fig.10. Forecasting product in need of repair demand in the pessimistic scenario

4.2.3. Demand forecasting model evaluation

In order to check the forecasting accuracy and the evaluation of SARIMA algorithm, the RMSE metric has been used. RMSE is calculated using the Equation (37):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y^\wedge)^2} \tag{37}$$

A lower Root Mean Square Error (RMSE) signifies better performance of the model, reflecting a smaller difference between the model's predicted output and the actual output.

Table 7 compares the RMSE values of the SARIMA and ARIMA models to assess their respective performances.

Table 7
The error of the prediction model is evaluated in comparison to other models

Product	Scenario	RMSE	
		SARIMA	ARIMA
Oxygen generator	Optimistic	9.21	24.01
	Probable	8.81	21.65
	Pessimistic	10.25	26.11
Blood storage refrigerator	Optimistic	11.21	18.91
	Probable	7.54	19.21
	Pessimistic	9.52	18.25
Oxygen generator need in repair	Optimistic	7.64	9.51
	Probable	7.99	10.21
	Pessimistic	8.56	10.56
Blood storage refrigerator need in repair	Optimistic	6.98	15.21
	Probable	7.56	14.87
	Pessimistic	8.78	21.22

Observing the results, it becomes evident that the SARIMA model outperformed the ARIMA algorithm in all prediction scenarios and demonstrated the most favorable outcomes.

4.3. Computational results

In this section, the results obtained from presented content covers the resolution of the mathematical model. In this regard, note that in order to solve the problem using MGP, it is necessary to solve several sub-problems and then solve the final problem. Figure 11 shows the process of solving the problem and the results obtained. It should be noted that in order to solve the problem, according to the literature and experts' opinion, the weight of the first OF is equal to 0.4 and the weight of the second and third OFs is considered equal to 0.3. According to Figure 11, production center 1 with technology 1 and production center 3 with technology 2 have been established. On the other hand, distribution centers number 2, 3, and 4 have been opened. On the other hand, collection centers number 1 and 2 have been established. Finally, repair center 1 with technology 2 and repairing center 3 with technology 2 have been opened. In addition, Table 8 shows the transportation modes used between facilities.

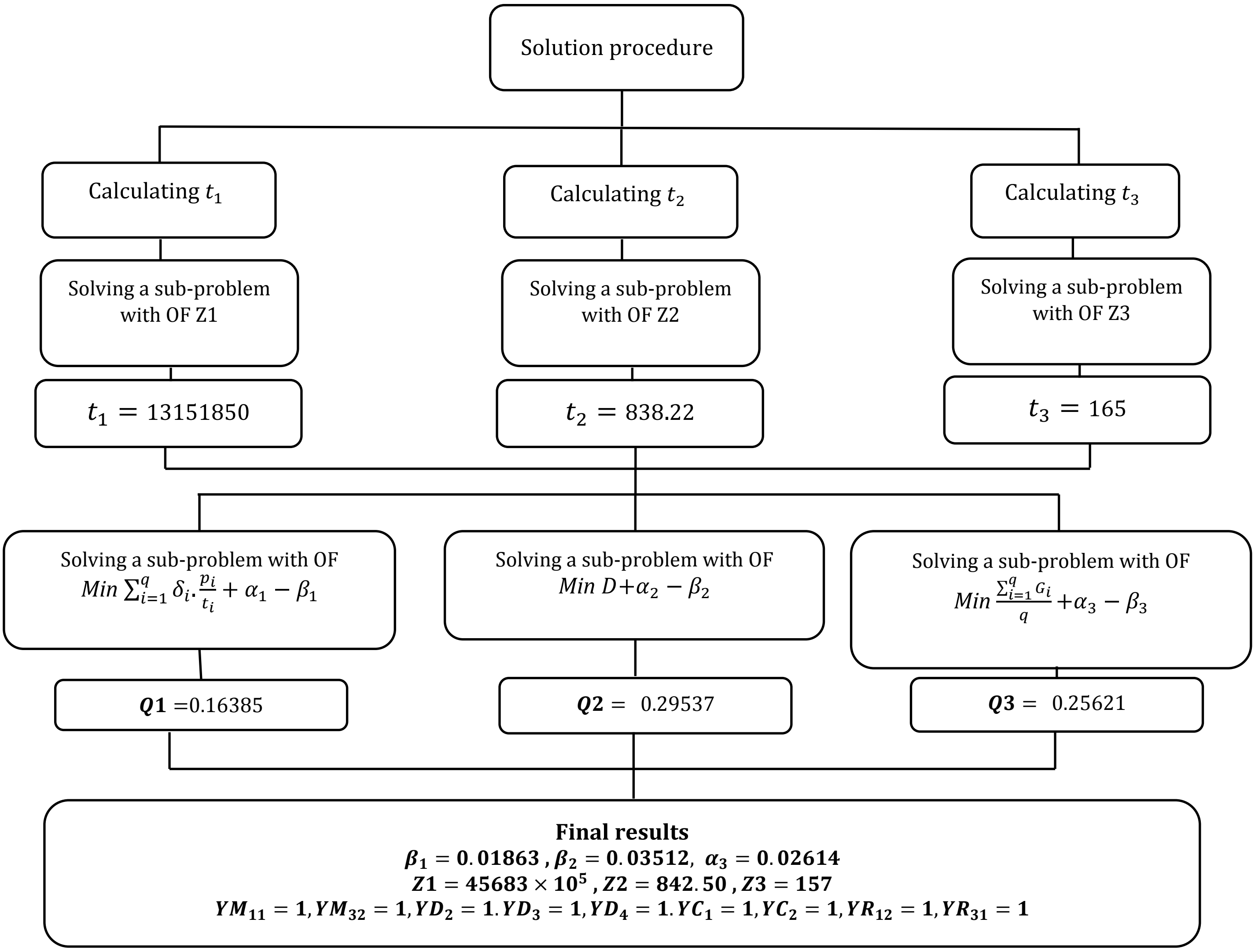

Fig. 11. The results of solving the research problem

Table 8
The utilized transportation modes

Facility-Facility	TM		
	1	2	3
PC – DC		✓	✓
DC - Customer	✓	✓	
Customer – CC		✓	
CC - RC	✓	✓	
CC - Disposal center	✓		
RC – DC	✓	✓	
RC - Disposal center	✓		

4.4. Sensitivity analysis

4.4.1. Demand

To show the impact of the demand on the outputs, the proposed MOM has been solved under different values from parameter. Figure 12 shows the results of the sensitivity analysis. As shown in this figure, by increasing the demand, the values of all OFs increase. With the increase in the demand parameter, to maintain the service level of the supply chain, more facilities should be established, and also more production and distribution activities are required. Moreover, by increasing the demand, transportation activities increase, too. Hence, the total cost has increased. Also, the increase in shortage costs can also be another reason for the increase in the first OF due to the increase in demand. On the other hand, for similar reasons, the increase in demand has led to an increase in the second OF (the amount of greenhouse gas emissions). Because when production and transportation processes increase, it is obvious that the amounts of related emissions will also increase. Finally, due to establishing more facilities by increasing the demand, the third OF has also increased.

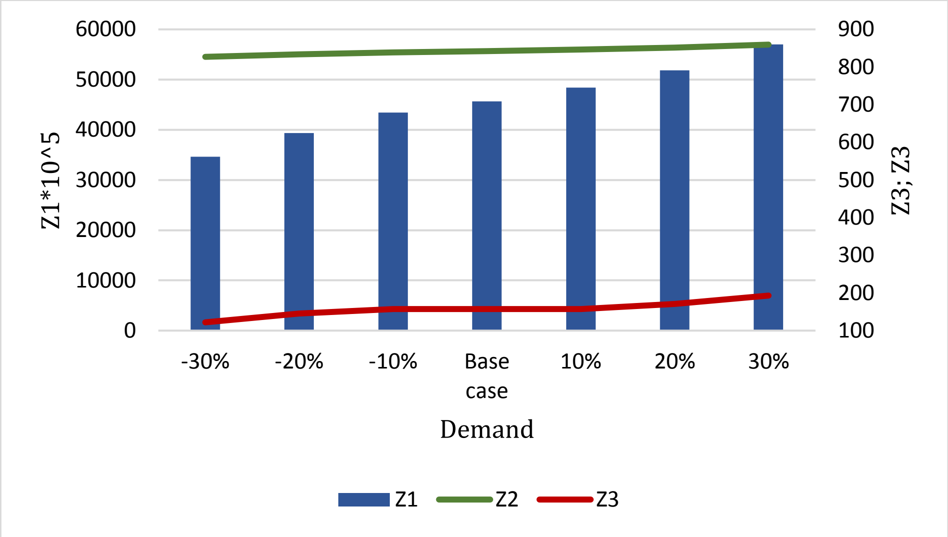

Fig. 12. The modus of the proposed MOM due to changing the demand

4.4.2. Capacity

Figure 13 shows the sensitivity analysis diagram of the first OF according to changes in the capacity parameter. According to this figure, increasing the amount of capacity significantly leads to the reduction of the total cost. The most important reason for this modus is that with increasing capacity, there is a need to establish fewer facilities. On the other hand, Figure 14 is the sensitivity analysis diagram of the OF according to changes in the demand parameter. According to Figure 14, increasing the amount of capacity leads to reducing the amount of pollution. Moreover, Figure 15 shows the sensitivity analysis of the third OF according to the capacity parameter. This figure shows that a 10% increase or decrease in capacity does not affect the third OF, but with an increase of more than 10% of the capacity, the value of the third OF decreases, and with a decrease of more than 10% of this parameter, the third OF increases.

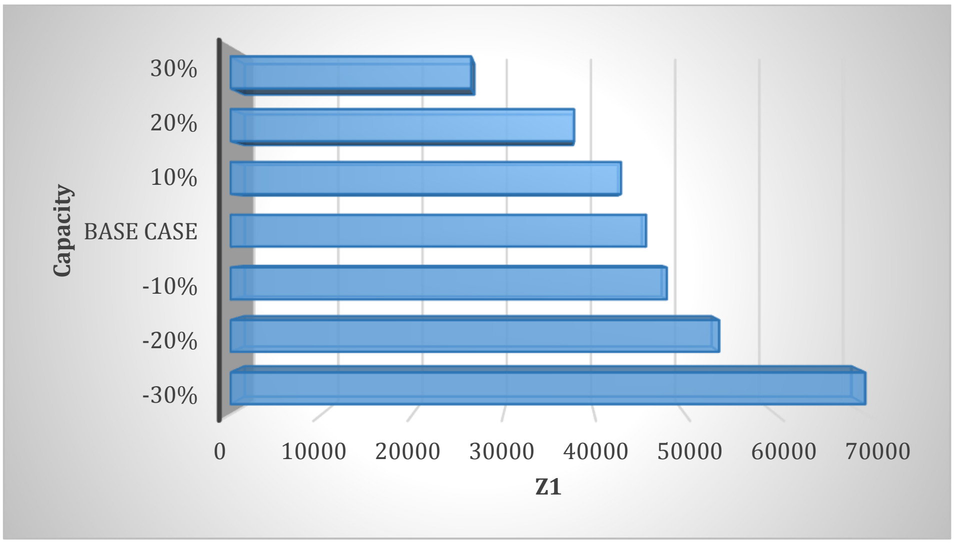

Fig. 13. The sensitivity analysis of the initial objective function (OF) is conducted based on the capacity parameter

Fig. 14. The sensitivity analysis of the second objective function (OF) is performed with respect to the capacity parameter

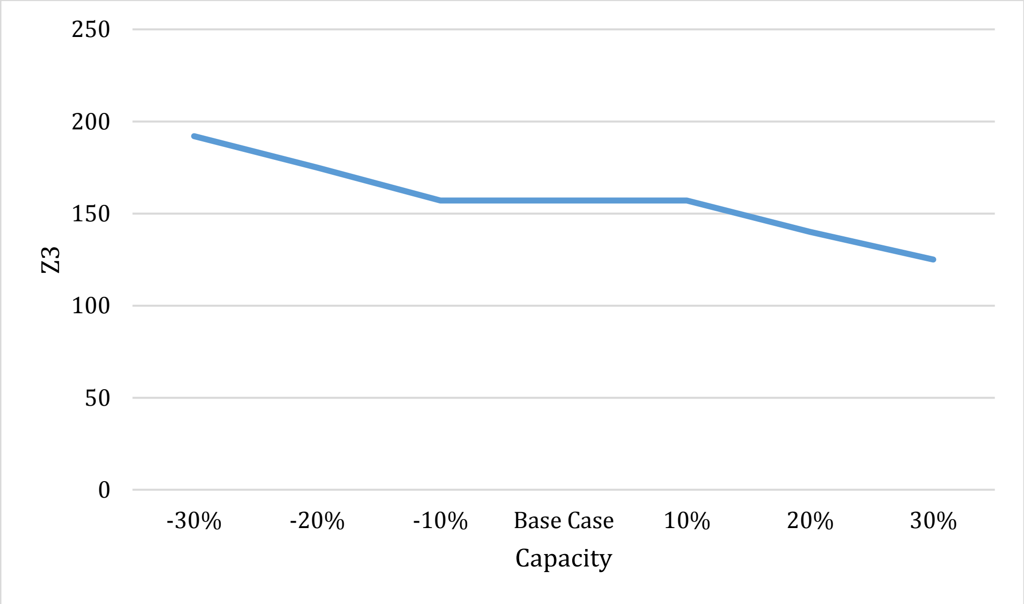

Fig. 15. The sensitivity analysis of the third objective function (OF) is carried out considering variations in the capacity parameter

4.4.3. sustainability and responsiveness interaction

In this section, the influence of the supply chain service level parameter on the sustainability factors is investigated. For this purpose, different values of the service level parameter are evaluated. In this regard, Figure 16 shows the sensitivity analysis diagram of the economic factor with respect to changing the service level parameter. Increasing the service level leads to increasing supply chain costs. Nevertheless, managers should be aware that although the reduction in the service level will lead to a reduction in costs, it can lead to customer dissatisfaction and a decrease in market share in the long term. On the other hand, the changes in the environmental factors according to the change in the service level are shown in Figure 17. According to Figure 17, an enhancement of the service level results in an increase in emissions, which is the main cause of this behavior is the increase in activities related to production and transportation. Finally, Figure 18 shows the behavior of the social factor according to the changes in the service level of the SC. The results indicate that the third OF (social factors) increases with the increase in the service level.

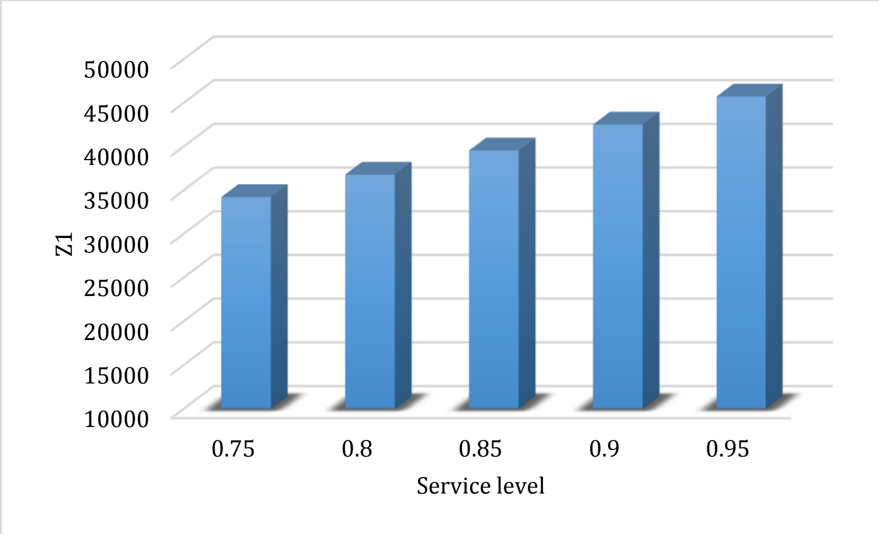

Fig. 16. The sensitivity analysis of the initial objective function (OF) is conducted based on variations in the service level parameter

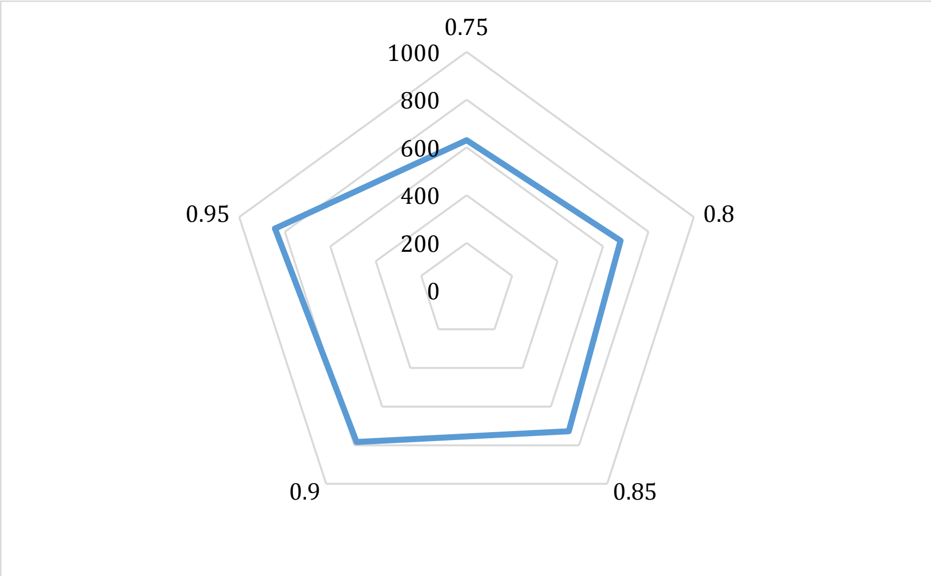

Fig. 17. The sensitivity analysis of the second objective function (OF) is performed with respect to changes in the service level parameter.

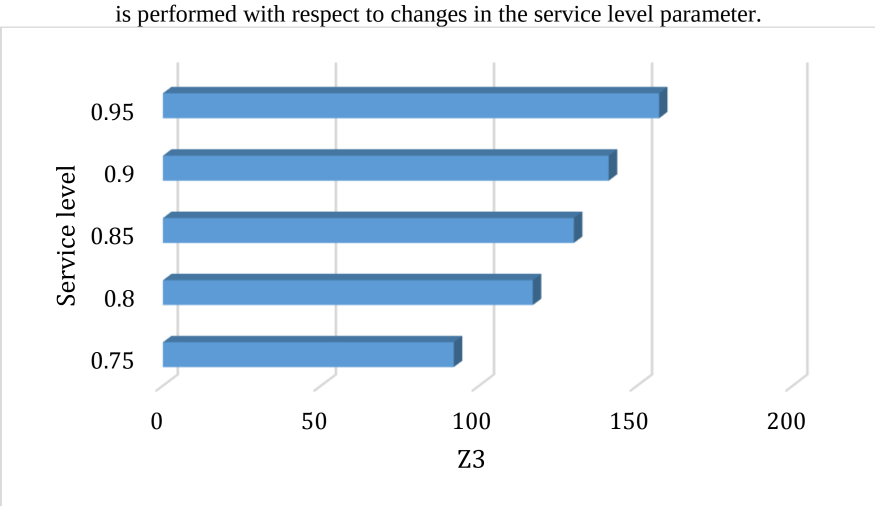

Fig. 18. The sensitivity analysis of the third objective function (OF) is carried out considering variations in the service level parameter.

4.5. Managerial insights

Over the years, supply chain networks have always been mentioned by researchers and experts in the direction of multidimensional supply chain optimization. In different periods, different paradigms affected supply chains according to different events. For example, around 2005-2010, the problem of resilience of supply chains became an important issue and the majority of researchers moved towards making supply chains resilient. But there is always a need for comprehensive development of supply chains in different sectors. For this reason, in recent years, the concept of sustainability entered the supply chains and examines and evaluates the supply chain in three environmental, economic and social dimensions. Therefore, considering the spread of the epidemic of COVID-19 in recent years and the impact of supply chains and businesses in different ways, it is important to pay attention to all paradigms of sustainability in the supply chain. This epidemic has caused the demand for medical products, especially oxygen generators and blood refrigerators, which are the studied products in the model of the present study, to undergo fundamental changes. These changes in demand have caused many suppliers to not be able to respond to the needs of customers. Therefore, it is important that in the design of SCN, the issue of accountability is always taken into consideration; In a supply chain, to what extent it is able to respond to the needs of customers. Therefore, in this article, the issue of accountability is also considered. Paying attention to the concepts of sustainability and accountability in supply chains has become very important in recent years, and the aim of this study is to answer this problem. But the most important point in the design of SCN is the existence of uncertainty in some important parameters such as demand. Various approaches to answer this uncertainty have been proposed in various articles and studies over the years; But in today's world, due to the vast amount of data available in supply chain networks, the use of data-driven algorithms in dealing with uncertainties is much better than other approaches. Combining data-driven algorithms with other methods such as robust optimization can increase the accuracy of parameter estimation. In this regard, in the present study, using data-driven algorithms and fuzzy stochastic optimization approach, the amount of demand has been estimated with appropriate accuracy according to different scenarios.
Since we have moved away from the era of the Corona epidemic in the current situation, it is not necessarily possible to estimate the amount of demand based on the data of the last 2-3 years. In this regard, a random approach has been used to change the amount of demand and available data based on different scenarios. Three optimistic, probable and pessimistic scenarios have been defined for the demand for oxygen generators and blood refrigerators; The optimistic scenario is when the demand for these products reaches its lowest level and the general health of the society is at its best. The probable scenario is like the conditions before the corona epidemic, where without extensive public health policies, the level of diseases is at a certain level, and the pessimistic scenario is like the era of the corona epidemic, when the amount of demand for the mentioned products reaches its maximum value.
According to the explanations given, for the SC to be responsive, it is necessary to be able to predict the demand and based on that, the structure and model of the supply chain network can be designed, which is well discussed in this article. In the real world, it is suggested that organizations always use data-driven and simulation approaches to predict the state of the supply chain in different conditions so that they can make more accurate decisions.

4.6. Theoretical Implications

This study introduces significant theoretical advancements by integrating sustainability and responsiveness within a closed-loop supply chain network (CLSCN) framework, particularly under mixed uncertainty. Previous research has often emphasized either sustainability or responsiveness separately, leaving a gap in a comprehensive approach that addresses both in tandem. By developing a multi-objective model that incorporates both aspects, this study extends the theoretical foundations of supply chain management to meet modern requirements for dynamic, sustainable, and responsive networks.
Moreover, this research contributes to theoretical literature by employing a data-driven framework that uses probabilistic risk simulation (PRS) combined with SARIMA, a model often underutilized in supply chain uncertainty modeling. Unlike traditional deterministic or scenario-based approaches, the data-driven model enhances accuracy in forecasting and responding to variability in demand and supply, which is critical for sustainable management. This framework supports a nuanced understanding of uncertainty management and lays the groundwork for applying data-driven methods more broadly within supply chain research.
Additionally, this study’s focus on the medical equipment industry offers insights into industry-specific complexities, particularly relevant in a post-COVID-19 context where demand fluctuations for medical supplies have been prominent. By addressing these fluctuations, the theoretical model developed here is applicable to other high-stakes industries facing similar challenges. In doing so, the study provides a valuable theoretical model for scholars and practitioners interested in optimizing closed-loop supply chains that are both resilient to market shifts and capable of meeting sustainability standards.

5. Conclusions

This study tackled the design challenge of Closed-Loop Supply Chain Networks (CLSCN) by focusing on two essential features: sustainability and responsiveness. To achieve this, a comprehensive data-driven decision-making model was developed. Initially, the study introduced a Multi-Objective Model (MOM) for configuring a CLSCN, which sought to optimize sustainability dimensions while incorporating measures for responsiveness. This integration is critical for modern supply chains, where balancing environmental impact, social responsibility, and

rapid response to demand changes are increasingly required.
To handle the inherent uncertainties in the model, a Probabilistic Risk Simulation (PRS) approach was applied, allowing for a more robust solution that accounts for variable demand and other unpredictable factors. Following this, the Seasonal Autoregressive Integrated Moving Average (SARIMA) method was employed to accurately estimate key parameters, further enhancing the reliability of the model. The final stage involved using a heuristic-based Meta-Goal Programming (MGP) approach, which provided an effective solution to the complex multi-objective problem.
The real-world applicability of the model was demonstrated through a case study involving the medical equipment industry, specifically focusing on the supply chain for oxygen concentrators and blood refrigerators. These products were chosen due to their high demand and critical role during public health crises, such as the COVID-19 pandemic. The results confirmed the model’s efficiency and performance, with findings indicating that increases in demand lead to higher costs and emissions, which, while challenging from an environmental perspective, positively impact the social dimension of the supply chain by improving service accessibility and job creation.
The analysis also revealed that higher service levels in the supply chain result in increased total costs and greenhouse gas emissions, underscoring the trade-offs that managers must consider when enhancing supply chain responsiveness. Additionally, increasing supply chain capacity demonstrated a positive impact on both economic and environmental objectives, as larger capacities can reduce total costs and emissions per unit, thanks to economies of scale and optimized operations.
Future research can expand on this model by incorporating additional features like resilience, agility, and globality, which are increasingly relevant in today’s interconnected and risk-prone global economy. Exploring alternative solution methods, such as Benders decomposition, could also help address the complexities of the proposed MOM. Furthermore, expanding the model to a multi-period framework and including inventory management concepts would allow for a more comprehensive approach to CLSCN design, making it adaptable to a broader range of real-world applications. These advancements would further enhance the model's applicability, offering greater insights into the sustainability and responsiveness trade-offs in supply chain design.

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Compliance with ethical standards

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