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ORIGINAL ARTICLE

An enhanced PSO algorithm to configure a responsive-resilient supply chain network considering environmental issues: a case study of the oxygen concentrator device

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Abstract
In recent years, the hyper-competitive marketplace has led to a drastic enhancement in the importance of the supply chain problem. Hence, the attention of managers and researchers has been attracted to one of the most crucial problems in the supply chain management area called the supply chain network design problem. In this regard, this research attempts to design an integrated forward and backward logistics network by proposing a multi-objective mathematical model. The suggested model aims at minimizing the environmental impacts and the costs while maximizing the resilience and responsiveness of the supply chain. Since uncertainty is a major issue in the supply chain problem, the present paper studies the research problem under the mixed uncertainty and utilizes the robust possibilistic stochastic method to cope with the uncertainty. On the other side, since configuring a supply chain is known as an NP-Hard problem, this research develops an enhanced particle swarm optimization algorithm to obtain optimal/near-optimal solutions in a reasonable time. Based on the achieved results, the developed algorithm can obtain high-quality solutions (i.e. solutions with zero or a very small gap from the optimal solution) in a reasonable amount of time. The achieved results demonstrate the negative impact of the enhancement of the demand on environmental damages and the total cost. Also, according to the outputs, by increasing the service level, the total cost and environmental impacts have increased by 41% and 10%, respectively. On the other hand, the results show that increasing the disrupted capacity parameters has led to a 17% increase in the total costs and a 7% increase in carbon emissions.

Keywords Responsive supply chain · Resilient supply chain · Green supply chain · Enhanced PSO

1 Introduction

Over the last two decades, due to the drastic increase in competition in both national and international markets, the importance of supply chain (SC) management has been highlighted, which led to enhancing the amount of research conducted in this field [1]. In the traditional approach, managers only considered the economic dimension of the SC while increasing the concerns about environmental impacts (EIs) of the SC has led to attracting the attention of researchers to design SC considering the environmental aspect that resulted in the development of green supply chain (GSC) [2–7]. In this regard, one of the ways to reduce EIs is incorporating the reverse logistics that lead to reusing the End-of-Use (EOU) or End-of-Life (EOL) products [8–10]. On the other side, one of the crucial concepts in the SC management area is responsiveness. In general, researchers described responsiveness as the ability

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of a network to satisfy customer demand due to fluctuations in demand over the planning horizon [11]. Responsiveness is an important metric that can significantly improve the productivity of an SC [11]. On the other hand, since the SCs usually exposed to natural and man-made disruptions, the role of resiliency strategies has been highlighted in modern businesses [12]. In the literature, the set of strategies to tackle the potential threats and recoil from disruptions is called resiliency [13, 14]. Although incorporating the resilience strategies may seem costly at first glance, ignoring this crucial concept may lead to an irreparable financial loss [12].

According to the crucial role of the mentioned issues, the present work configures an integrated forward and reverse SC considering resilience, responsiveness, and environmental dimensions. In this way, we propose a multi-objective mathematical model (MOMM) that minimizes the EIs and costs of the SC and also maximizes resilience and responsiveness. Then, to deal with the uncertainty of the SC problem, a robust possibilistic stochastic (RPS) optimization method is applied. Afterwards, due to the complexity of the research problem, a hybrid approach based on the LP-metric method and the enhanced particle swarm optimization (PSO) algorithm is developed to solve the proposed model. The main necessity of the current research is simultaneous consideration of the mentioned aspects (i.e. greenness, responsiveness, and resiliency) in the SC problem, which can dramatically improve the performance of the SC network. Also, another necessity of this study is to investigate the logistics activities of one of the crucial medical devices (MDs), which was widely used during the COVID-19 outbreak, namely the oxygen concentrator device. Regarding the benefits of the present work, we can say that managers of the SC, especially in the field of the MDs industry, can benefit from this study and give a very nice perspective on the importance and application of the three factors (i.e. greenness, responsiveness, and resilience) in the SC design problem. On the other hand, researchers can benefit from this work due to its theoretical contributions such as developing the enhanced PSO algorithm.

In general, the main objectives of the present research are as follows:

1. Proposing a MOMM to design a responsive-resilient SC with environmental considerations.
2. Tackling the hybrid uncertainty employing the robust possibilistic stochastic method.
3. Proposing an efficient algorithm to achieve the optimal/near-optimal solutions. In this regard, an enhanced particle swarm optimization algorithm is developed.

On the other hand, the main scope of this study is related to investigating the SC network design problem by considering three crucial metrics, namely the EIs, responsiveness, and resiliency.

In the following, the literature is reviewed in Sect. 2. The research problem is formulated in Sect. 3. The methodology of this paper is provided in Sect. 4. The computational results are presented in Sect. 5. Eventually, conclusions are provided in Sect. 6.

2 Literature review

This section is dedicated to reviewing the related literature in three parts: (1) green SC, (2) resilient SC, and (3) responsive SC. Then, we categorize the existing studies and provide the research gaps and contributions.

2.1 Green SC

In general, when environmental issues are considered in the SC network problem, the traditional SC shifts to a green one. In recent years, the green SC problem has attracted the attention of researchers, and in this part, we report some of the related works in this area.

Rad and Nahavandi [15] proposed a model to configure a green closed-loop SC (CLSC) network considering discount. The offered model minimized the costs and EIs while maximizing customers' satisfaction. Boronoos et al. [16] presented a multi-objective MINLP model to design a green SC network under uncertainty to reduce the total costs (TCs) and EIs. They developed a robust approach to cope with epistemic uncertainty and flexible constraints. Considering the case study of the copier industry, the authors obtained the optimal solution using the Torabi and Hassini [17] approach. Zhen et al. [18] investigated the green and sustainable SC network problem by proposing a scenario-based bi-objective model with uncertain demand. The suggested model minimized the EIs and the TCs, simultaneously. It should be noted that the authors utilized the Lagrangian relaxation approach to handle the problem. Yavari et al. [19] proposed a Multi-Objective Mixed Integer Programming (MOMIP) model to design a multi-period multi-product green SC under uncertainty for perishable products of a dairy company. The main aims of the proposed model are total cost and EIs minimization. The robust optimization (RO) approach is employed to cope with uncertain parameters, including demand, returned products' quality and rate of return. Mardan et al. [20] configured a green SC network by presenting a mathematical model. The authors aimed to minimize TCs and environmental emissions through the optimal choice of the location and amount of transportation. The proposed model was solved by combining the LP-metric method and Benders' decomposition. The application of the suggested model is investigated through a case study of a wire-and-cable industry. Rahimi and Fazlollahtabar [21] offered a mixed-integer programming model to design a green CLSC considering different product quality levels and pricing policies. The main objective of the proposed model is total profit maximization. The proposed network includes suppliers, producers, distributors, and consumers in the forward SC, and in the reverse SC consists of the collection, recycling, and disposal centres. To solve the research problem, two metaheuristic algorithms, i.e. particle swarm optimization and genetic algorithm, were developed. Yu and Khan [22] presented a stochastic fuzzy programming model for designing an environmental-friendly SC to minimize EIs and the total cost. They applied the ε-constraint approach to solve the suggested model. Gholizadeh and Fazlollahtabar [23] offered a mathematical model to develop a green CLSC for the melting industry. The proposed model's main objective is to maximize total profit while considering environmental aspects. The authors utilized the RO method to cope with the uncertainty and solved the research problem by developing a modified genetic algorithm. Sharif et al. [24] investigated the integrated green SC network design and routing problems. They proposed a mathematical model and developed a simulated annealing algorithm to handle the suggested model. Homayouni et al. [25] offered a RO model to design a green-sustainable SC network considering different types of vehicles and carbon emission policies. That research attempts to minimize the total cost of the network and EIs. The authors combined the goal programming approach and a heuristic method to handle the complexity of the problem in solving process.

2.2 Resilient SC

In general, resiliency includes a set of strategies to cope with potential disruptions [26]. Due to the importance of this phenomenon, there have been several works in this field in recent years. For example, Yavari and Zaker [8] investigated the resilient SC network design problem considering environmental issues. The authors suggested a stochastic MOMIP for minimizing the EIs and the TCs. They incorporated resiliency in their model by considering different resilient strategies involving the intermediate facility, integrating interdependent networks, keeping emergency stock, lateral transshipment, and reserving extra capacity. They used the LP-metric approach to obtain the solution. Fazli-Khalaf et al. [27] offered a flexible-possibilistic model to design a CLSC considering resiliency and sustainability features under mixed uncertainty. The suggested model attempted to minimize the EIs and TCs and maximize the facilities' operational reliability and social impacts. The authors incorporated resiliency in the problem by considering the reliability of the facilities. Bottani et al. [28] developed metaheuristic algorithms to configure a resilient food SC for maximizing profits and minimizing delivery times. The proposed MOMIP model is solved using ant colony optimization (ACO) algorithm. The effectiveness of the presented model is shown through a case study of readymade UHT tomato sauce. Hosseini-Motlagh et al. [29] configured a resilient and sustainable SC network for the power industry. The authors offered a robust possibilistic model for maximizing resiliency and social impacts and minimizing the TCs. The authors solved the model employing the goal programming approach. Mohammed et al. [30] proposed a mixed framework based on the mathematical model and the fuzzy AHP method to design a green-resilient SC network. At first, the author calculated the weights of resiliency criteria using the fuzzy AHP method and then designed the network by suggesting a model. They employ the ε-constraint method to solve the research problem. Taleizadeh et al. [31] combined the mathematical programming model and the game theory method to design a resilient supply chain network in a competitive environment. They defined resilience in the problem based on disruption scenarios and surplus inventory strategy. Eventually, the authors solved the problem using a decomposition method. Mehrjerdi and Shafiee [32] presented a model for designing a resilient SC network considering sustainability for the tire industry. The main goals of the offered model were minimizing the EIs and TCs while maximizing the social impacts. At the outset, they used the TOPSIS approach to rank the resiliency strategies and then employed the ε-constraint approach to obtain the solution. Namdar et al. [12] developed a multi-stage framework to configure a resilient SC network. The authors firstly identified the resilience measures and then calculated those scores. Afterwards, they offered a model to configure a resilient SCN. The proposed multi-echelon, multi-product resilient SC is studied under disruption and operational risks. The proposed mixed possibilistic–stochastic programming model is solved by utilizing the branch and bound algorithm. Gurobi. Hasani et al. [33] offered a MOMIP for configuring a green and resilient SC network. The suggested model minimized the amount of pollution and the TCs and maximized the network resilience. They used metaheuristic algorithms to solve the mathematical model and showed the performance of the model and algorithms by solving several examples. Mamashli et al. [34] proposed a MOMIP model to design a sustainable–resilient debris SC network under mixed uncertainty. The main aims of the proposed model are EIs, TCs, and transportation risks minimization as well as social impacts maximization. To tackle the hybrid uncertainty, the fuzzy robust stochastic (FRS) optimization model was applied. The authors solved the model by developing a hybrid algorithm based on the goal programming approach and the PSO algorithm.

2.3 Responsive SC

As aforementioned, the ability of an SC to handle fluctuations of demand was defined as responsiveness. Recently, several works have been conducted in this field. For example, Pishvaee and Rabbani [35] presented two mathematical models to design a responsive, multi-stage network for minimizing the TCs. In one of the models, a direct shipment was permitted. On the other side, direct shipment was not allowed in another model. Then both of the SC problems considered in this study are modelled by a bipartite graph to escape the complexity of MIP mathematical models. They compared the mentioned models to examine the impact of direct transport on the responsiveness of the SC network. The authors also developed a heuristic algorithm based on graph theory to solve the proposed model. Baghalian et al. [36] offered a model to design a resilient and responsive SC network. They incorporated resiliency according to disruption scenarios and defined responsiveness according to the service level. To tackle uncertainty, the authors applied the scenario-based RO method. Eventually, the authors solved the problem by considering a case study in the rice industry using an approximate method. Rabbani et al. [11] designed a responsive SC network by offering a mathematical model to minimize the TCs. They considered lateral transshipment as a responsiveness measure and solved the research problem using a heuristic method. Azaron et al. [37] presented a multi-stage multi-objective stochastic programming model to design a responsive SC network under uncertainty. The main objectives of the proposed model were to minimize total travel time and maximize the responsiveness of the proposed model. In their study, the responsiveness was defined based on the lead time of the SC. Sabouhi et al. [38] suggested a stochastic MOMIP to configure a responsive and resilient SC network to minimize the TCs under uncertainty. To improve the resilience of the system, the authors considered the extra production capacities, backup suppliers, lateral transshipment, and multiple transport routes. Hamideh et al. [39] proposed a robust stochastic optimization model to configure a responsive SC. The proposed model minimized the lead time and the TCs. A robust possibilistic programming approach is employed to tackle uncertainty in the suggested model. It should be noted that the authors used the ε-constraint approach to solve offered model. Nayeri et al. [40] developed a forward supply chain considering the sustainability, resiliency, and responsiveness metrics. To cope with the hybrid uncertainty, they used the FRS. Also, they employed the meta goal programming method to solve the proposed MOMIP. Fattahi et al. [41] offered a stochastic MOMIP to configure a responsive and resilient SC network to minimize the TCs. They defined resilience in the disruption scenarios and incorporated responsiveness according to the rate of satisfied demand over potential demand. The proposed model is solved using GAMS.

2.4 The classification of the existing approaches

In this section, we try to classify the existing approaches. In this regard, Table 1 categorizes the approaches of the most related studies.

2.5 Critical appraisal of the existing approaches

According to the reviewed literature, there are many studies which are investigated the forward and reverse SC networks. However, some critical aspects such as greenness, responsiveness, and resiliency, along with considering reverse flow, have been less discussed in the previous studies by the researchers. On the other side, at any point within a supply chain network, uncertainty might arise. This uncertainty might be due to man-made or natural disasters like earthquakes, floods, etc., or business-as-usual uncertainties such as customers' demands, operational costs, the capacity of facilities. Yet, mixed uncertainty as one of the main challenges in the SC problem has been overlooked so far.

For example, in the proposed model by Rad and Nahavandi [15], only the aspect of greenness is incorporated in their CLSC network, while resiliency, responsiveness, and uncertainty, which are key factors in designing SCs, were overlooked. Boronoos et al. [16] developed their multi-objective MINLP model under uncertainty considering the green factors of SC. They used a robust flexible-possibilistic programming approach to only tackle uncertainty caused by the business environment and ignored the importance of uncertainties caused by natural/man-made disasters. Moreover, by studying the problem under mixed uncertainty, they could have developed a more practical and realistic model. In addition, in their offered model, the significant impacts of resilience strategies and responsiveness on SC networks have also been neglected. In the proposed models by Zhen et al. [18] and Yavari et al. [19], a bi-objective mathematical model under uncertainty was suggested in which only the greenness aspect of SC is included. They were ignorant, like Boronoos et al. [16] study, about the implications of not considering mixed uncertainty, resiliency, and responsiveness on SC networks. Ghomi-Avili et al. [42] offered a bi-objective model for configuring a green competitive CLSC under uncertainty. They incorporated the concept of resilience by considering disruptions, yet, by considering

Table 1 Classifying the existing works

Paper	The considered dimensions in the model			Uncertainty modelling	Solution method
	Greenness	Resilience	Responsiveness		
[16]	✔	–	–	Robust flexible-possibilistic programming	Torabi and Hassini
[18]	✔	–	–	Scenario-based programming	Lagrangian relaxation
[19]	✔	–	–	Robust optimization	Heuristic
[42]	✔	✔	–	Fuzzy model	Fuzzy programming technique
[8]	✔	✔	–	Scenario-based programming	LP-metric
[31]	✔	✔	–	–	Decomposition method
[12]	–	✔	–	Mixed possibilistic–stochastic programming	Branch and Bound algorithm
[27]	✔	✔	–	Flexible-possibilistic model	ε-Constraint
[32]		✔		Scenario-based programming	ε-Constraint
[33]	✔	✔	–	Scenario-based programming	Metaheuristic algorithms
[43]	✔	✔	–	Robust fuzzy programming	Goal programming
[41]	–	✔	✔	Scenario-based programming	GAMS
This work	✔	✔	✔	Robust possibilistic stochastic (mixed uncertainty)	Enhanced PSO

multiple resiliency strategies such as back-up suppliers and adding extra capacity simultaneously, they could have developed a more competitive and reliable SC network. In their study, the significant impact of responsiveness and mixed uncertainty was overlooked. In the proposed SC network by Yavari and Zaker [8] and Taleizadeh et al. [31], resiliency and green factors of SC are considered. Resiliency is considered in their problem by simultaneous consideration of different resiliency strategies to tackle unwanted disruptions. The superiority of [8] model over [31] model is that in the [8], both forward and reverse flow were considered, but in the proposed model by [31], only the forward flow was considered. However, responsiveness and mixed uncertainty, which are of high importance in SC network design, were neglected by the authors. In the presented model by Namdar et al. [12], only the resilience dimension is considered. The greenness aspect, which is a major concern due to the environmental crisis worldwide, is not considered in their proposed model. It should be noted that the proposed model also lacks the other crucial factors, responsiveness and mixed uncertainty. In the proposed models by Rabbani et al. [11] and Pishvaee and Rabbani [35], only economic objectives are considered and the authors did not consider the importance of green factors in SCs and were negligent regarding environmental issues. Moreover, despite the importance of resilience strategies and mixed uncertainty, the authors also did not incorporate these factors in their model. Fazli-Khalaf et al. [27], Mehrjerdi and Shafiee [32], and Hasani et al. [33] considered the green factors and resilience strategies in their proposed model. The advantage of the [27] and [33] models over [32] is that they studied their models under uncertainty caused by the business environment. Nevertheless, they could have enhanced their proposed model by developing a mathematical model under mixed uncertainty and considering the concept of responsiveness in their presented network. In Baghalian et al. [36] study, disruption scenarios are incorporated to make the proposed model resilient and service level is defined to include the responsiveness concept. Their study was investigated under demand uncertainty and used scenario-based RO methods to tackle uncertainty. Meanwhile, they could have taken into account multiple resilience strategies simultaneously as well as mixed uncertainty to make the proposed model more reliable. Also, their proposed model did not consider the green factors of the SC network. Fattahi et al. [41] gave a resilient and responsive SC network, in which responsiveness was incorporated into the problem by the rate of met demand over total demand and resiliency in the disruption scenarios. The proposed model only considered the economic aspect of the SC and did not include SC's green factors. In addition, in their proposed model, the significant impacts of studying SC under mixed uncertainty have also been overlooked.

Compared to the previous papers, we have incorporated the green aspect of SC by considering the re-use of EOU products (reverse logistics) and carbon emission minimization. We incorporate the concept of resiliency in the research problem by considering the effect of disruption scenarios, backup suppliers, and extra capacity. Moreover, by defining a minimum service level for the SC, the concept of responsiveness is also included. Meanwhile, it can be seen in the related literature (designing an SC network with different features such as responsive-resilient SC) that mixed uncertainty and reverse logistics have been rarely addressed by the researchers. In this regard, this paper considers reverse logistics in the proposed network and also investigates the problem under mixed uncertainty. Additionally, since the SCN configuration is known as an NP-Hard problem [44–46], this research develops an enhanced particle swarm optimization algorithm to solve the proposed model. It should be noted that since producing and transporting the mentioned products lead to generating greenhouse gases, the green aspect is relevant to this product. On the other side, since the vulnerabilities of today's industry have been exacerbated during the recent pandemic, the resilient concept is relevant to this product. Eventually, since there is a dramatic increase in the demand for MDs in the coronavirus disease, the responsiveness measure is relevant to this product. In general, the main contributions of this research can be summarized as follows:

1. As aforementioned, simultaneous consideration of green, responsive, and resilient factors in the SC network problem has been rarely addressed by previous researches. Hence, this study attempts to consider responsiveness, resiliency, and environmental issues in the SC network problem, simultaneously.
2. The present work is the first study that configures an integrated forward and reverse green-responsive-resilient SC network.
3. As shown in Table 1, capacity planning, technology selection, and carbon policy have been rarely addressed in the previous similar paper. In this regard, this research incorporates the mentioned concepts in the proposed model.
4. This paper investigates the problem under mixed uncertainty and employs the RPS method to tackle it. It should be noted that the mixed uncertainty has been incorporated by considering scenario-based, fuzzy, and fuzzy-scenario parameters.
5. This study develops an efficient algorithm (enhanced PSO) to solve the research problem due to the NP-hardness of the proposed model.
6. This research investigates the oxygen concentrator device as a case study due to its crucial role in the COVID-19 outbreak.

3 Study methodology

3.1 Problem definition

This study aims to configure a green-responsive-resilient SC network by considering the case study of the oxygen concentrator. The SC network that configured in this study involves 4 echelons in the forward SC consisting of primary suppliers (PSs), backup suppliers (BSs), manufacturing centres (MCs), distribution centres (DCs), and demand points (DPs); and four facilities in the reverse SC consisting of collection centres (CCs), repairing centres (RCs), second-hand market, and disposal centres. PSs and BSs are responsible for providing the required raw materials. On the other side, MSs and DCs, respectively, aim at producing and distributing the goods. The main duty of CCs is to collect the EOL and EOU goods from the customers. RCs are responsible for repairing the collected products, and finally, disposal centres aim to dispose of the waste.

The materials and products flow in the proposed SCN are as follows. First, the required raw materials are shipped from the suppliers to the MCs. It should be noted that if the PS cannot provide the needed raw materials, for any reason, the firm can supply the raw materials from the BS. After producing goods in the MCs, they are shipped to DCs for sending to DPs. In the backward flow, the returned goods are collected and inspected by CCs. The repairable products are sent to the RPs and then to the second-hand market. On the other side, the unrepairable products are sent to disposal centres. It should be noted that the RPs can be opened with different technologies, and the RP with less pollution has more setup cost. Figure 1 shows the conceptual outline of the research problem, and Fig. 2 depicts the designed SC network.

On the other hand, the problem is investigated under the capacity-trade carbon emission policy. According to this policy, each company is allowed to emit a predefined amount of carbon. If the company emits less carbon than the specified capacity, the extra credit can be sold in the market. Nevertheless, if the company needs to produce more carbon than the predefined capacity, it has to buy the amount of carbon credit. For reading more detail about this policy, interesting readers can see [47]. On the other side, the main dimensions of the research problem (environmental, responsiveness, and resilience) are defined as follows:

- In this study, the environmental aspect of the SC is incorporated by considering reverse logistics and reducing GHG emissions (i.e. reducing greenhouse gases). To see other studies that considered these factors as EIs of the SC, interested readers can refer to [21, 48–50]. On the other side, in general, since considering more other environmental factors might drastically increase the uncertainty of the problem, we considered the most important environmental factors based on our problem definition and case study. Considering reverse logistics and minimizing carbon

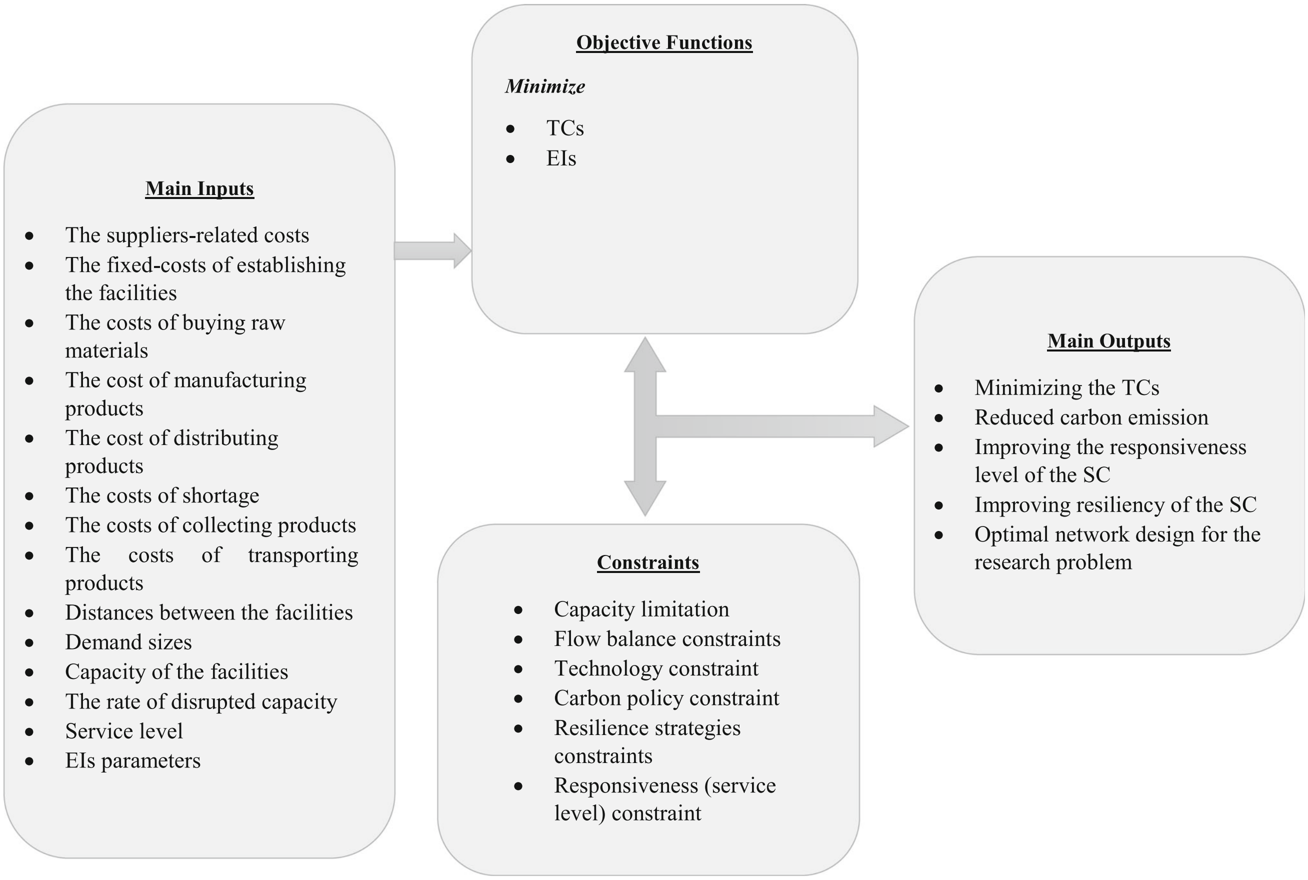


Fig. 1 A conceptual outline of the research problem

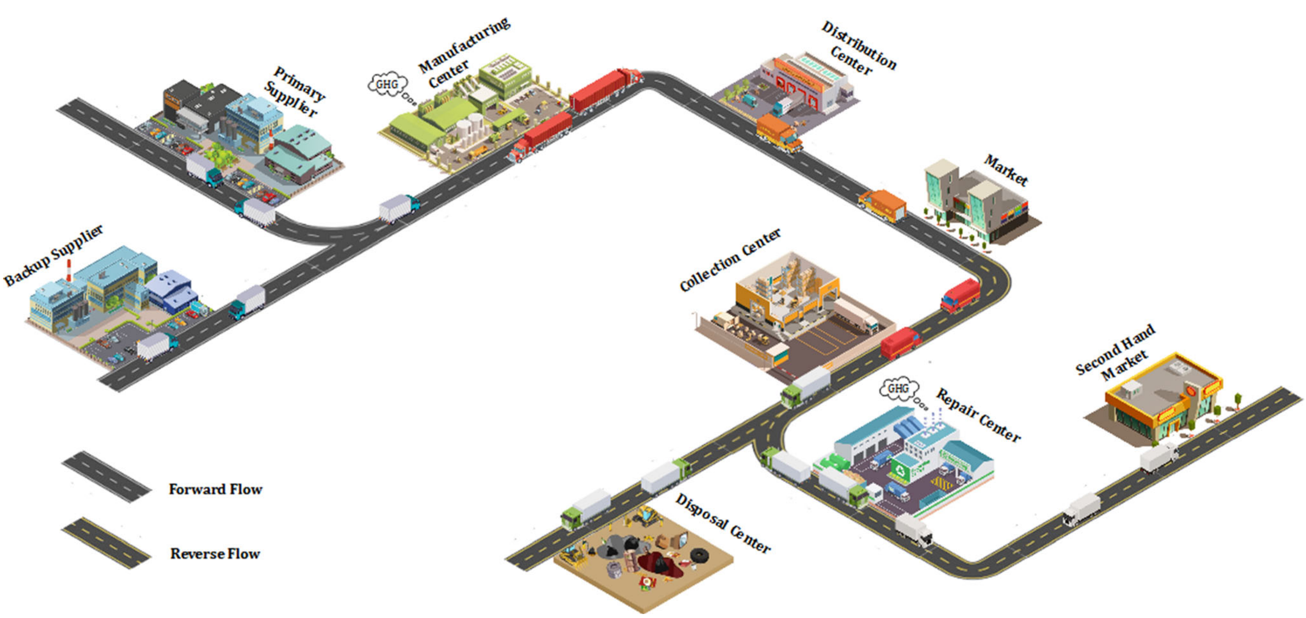


Fig. 2 The designed SC network

emissions are two widely considered factors in previous similar studies (see [2, 23, 25, 27, 34, 43, 51, 52]).

- Similar to Sabouhi et al. [38], this research considers the responsiveness dimension by defining a minimum service level for the SC.

- This paper defines the resilience dimensions in the problem by considering disruptions scenarios (like [8, 36, 53]), backup suppliers (like [54–56]), and extra capacity (like [38, 57, 58]).

3.2 Assumptions

This research considers the following assumptions for formulating the problem.

- The location of the facilities of the SC is known.
- Capacity of the facilities is limited and the problem is investigated under capacity constraints.
- Shortage (lost sales) is allowed.
- The service level is defined on the main market (not the second-hand market).
- The problem is studied under the carbon cap-and-trade policy.
- The problem is investigated under mixed uncertainty.

3.3 Mathematical model

In this section, the mathematical model is provided. The notations of the model have been presented in Supplementary material.

Here, to better understand the nature of the proposed model, we define the main features of the problem using the verbal definition in the following. It should be noted that such a complex model to investigate the correlation and dependencies among green-resilient, green-responsive, and resilient responsive factors previously developed by researchers (see [34, 38, 51, 52, 54]). However, this study aims at investigating green-resilient-responsive factors.

- **Economic aspect:**

In this research, the economic aspect is defined by minimizing the TCs of the SC network in the first objective function. The TCs are as follows:

$$\begin{aligned}&\text{Minimizeing the total costs} = \text{costs of contracting to suppliers}\\&\quad + \text{costs of opening facilitiescosts of purchasing raw materials}\\&\quad + \text{production costs} + \text{distributing costs} + \text{shortage costs}\\&\quad + \text{collecting cost}\\&\quad + \text{repairing costs} + \text{disposal costs} + \text{adding extra capacity cost}\\&\quad + \text{transportation costs} + \text{carbon - related costs}\end{aligned}$$

- **Environmental aspect:**

The environmental aspect is considered in two ways. On the one side, the problem considers reverse logistics to reuse the EOU products. On the other side, the model tries to minimize total carbon emissions in the second objective function. It should be noted that since one of the main manufacturing (and repairing) activities of the considered product (the oxygen concentrator device) is welding, which leads to emitting carbon, we aim to minimize the carbon emission in this study. The carbon emitted by the SC network is as follows:

$$\begin{aligned}&\text{Minimizing the environmental impacts}\\&\quad = \text{carbon emission due to production activities}\\&\qquad + \text{carbon emission due to repairing activities}\\&\qquad + \text{carbon emission due to transportation activities}\end{aligned}$$

- **Responsiveness aspect:**

This study considers responsiveness by defining a minimum service level value. Based on this definition, the rate of met demand over total potential demand must be greater than the minimum service level. The mentioned point is calculated according to relation (2):

$$\frac{\sum_{k,d,s} .ADD_{kds}}{\sum_{d,s} \widetilde{Dem}_{ds}} \geq \alpha \tag{1}$$

- **Resilience aspect:**

In this paper, to incorporate the resilience strategies, we consider disruption scenarios (considering the disrupted rate of facilities' capacity in each scenario), backup supplies (see variable $YSB_{i'}$ and corresponding parameters), and extra capacity for MCs (see variable $ECAP_{js}$).

Here, the mathematical model is proposed. Relation (2) shows the first Objective Function (OF) that minimizes the TCs. In this equation, $\widetilde{FSP}_i$ and $\widetilde{FSBP}_{i'}$ are Fixed costs (FC) of working with the primary and backup suppliers, respectively. YS_i and $YSB_{i'}$ show that whether PS and BS are selected or not. $\widetilde{FDC}_{kl}$ is the FC of establishing the DCs, and YD_{kl} denotes whether the DC is established or not. $\widetilde{FCC}_{cl}, YC_{cl}$, $\widetilde{FRC}_{tl}$, and YR_{tl} have a similar definition for CCs and RCs, respectively. PS_s is the probability of occurrence of scenarios. $\widetilde{HM}_{ri} and \widetilde{HMB}_{ri'}$ show the buying cost of the raw materials, and ASM_{rijs} and $ASBM_{ri'js}$ represent the quantity of the purchased raw materials. $\widetilde{HT}_j$ and AMD_{jks} are the production costs and the quantity of production, respectively. On the other side, $\widetilde{HD}_k$ and ADD_{kds}, respectively, show the distribution costs and the quantity of the distributed products. $\widetilde{HK1}_d, SH_{ds}, \widetilde{HK2}_g$, and BB_{gs} are the parameters and variables related to the shortage. $\widetilde{HC}_c$ and ADC_{dcs}, respectively, represent the collection cost and the quantity of the collected products. $\widetilde{HR}_{tq}, ACR_{cts}$ are the repairing cost and the quantity of the repaired products. $\widetilde{HD}_b$ is the disposal costs, and ACB_{cbs} is the quantity of products that should be disposed of. $\widetilde{HEC}_j$ and $ECAP_{js}$ are, respectively, show the cost of adding the extra capacity and the quantity of the extra capacity. $\widetilde{TC}$ is the unit of transportation cost and d denotes the distance between the facilities. Finally, $\widetilde{cp}, PC_s$, and SC_s, respectively, show the carbon price, the quantity of the purchased carbon credit, and the quantity of the sold carbon credit.

$$\begin{aligned}
MinZ1 = & \sum_i \widetilde{FSP}_i \cdot YS_i + \sum_{i'} \widetilde{FSBP}_{i'} \cdot YSB_{i'} \\
& + \sum_{k,l} \widetilde{FDC}_{kl} \cdot YD_{kl} + \sum_{c,l} \widetilde{FCC}_{cl} \cdot YC_{cl} \\
& + \sum_{t,l} \widetilde{FRC}_{tl} \cdot YR_{tl} \\
& + \sum_s PS_s \Bigg(\sum_{r,i,j} \widetilde{HM}_{ri} \cdot ASM_{rijs} + \sum_{r,i',j} \widetilde{HMB}_{ri'} \cdot ASBM_{ri'js} \\
& + \sum_{j,k} \widetilde{HT}_j \cdot AMD_{jks} \\
& + \sum_{d,k} \widetilde{HD}_k \cdot ADD_{kds} + \sum_d \widetilde{HK1}_d \cdot SH_{ds} + \sum_g \widetilde{HK2}_g \cdot BB_{gs} \\
& + \sum_{c,d} \widetilde{HC}_c \cdot ADC_{dcs} + \sum_{c,t,q} \widetilde{HR}_{tq} \cdot ACR_{cts} + \sum_{b,c} \widetilde{HD}_b \cdot ACB_{cbs} \\
& + \sum_j \widetilde{HEC}_j \cdot ECAP_{js} \\
& + \widetilde{TC} \Bigg(\sum_{i,j,r} d_{ij} \cdot ASM_{rijs} + \sum_{i',j,r} d_{i'j} \cdot ASBM_{ri'js} + \sum_{j,k} d_{jk} \cdot AMD_{jks} \\
& + \sum_{k,d} d_{kd} \cdot ADD_{kds} + \sum_{d,c} d_{dc} \cdot ADC_{dcs} + \sum_{c,t} d_{ct} \cdot ACR_{cts} \\
& + \sum_{c,b} d_{cb} \cdot ACB_{cbs} \\
& + \sum_{b,g} d_{bg} \cdot ARG_{tgs} \Bigg) + \widetilde{cp} \cdot PC_s - \widetilde{cp} \cdot SC_s \Bigg)
\end{aligned} \tag{2}$$

The second OF (Eq. 3) minimizes the total EIs of the SC network, where $\widetilde{Mei}$ is the EIs (EI) of manufacturing products, $\widetilde{Rei}_q$ shows the EI of repairing products, and $\widetilde{Tei}$ represents the EI of transporting products.

$$\begin{aligned}
\text{Min } Z2 = & \sum_s PS_s \Bigg(\sum_{j,k} \widetilde{Mei} \cdot AMD_{jks} + \sum_{c,t,q} \widetilde{Rei}_q \cdot ACR_{cts} \\
& + \widetilde{Tei} \cdot \Bigg(\sum_{i,j,r} d_{ij} \cdot ASM_{rijs} + \sum_{i',j,r} d_{i'j} \cdot ASBM_{ri'js} \\
& + \sum_{j,k} d_{jk} \cdot AMD_{jks} \\
& + \sum_{k,d} d_{kd} \cdot ADD_{kds} + \sum_{d,c} d_{dc} \cdot ADC_{dcs} \\
& + \sum_{c,t} d_{ct} \cdot ACR_{cts} + \sum_{c,b} d_{cb} \cdot ACB_{cbs} \\
& + \sum_{b,g} d_{bg} \cdot ARG_{tgs} \Bigg) \Bigg)
\end{aligned} \tag{3}$$

Constraint (4) is to calculate the amount of the purchased raw materials. It should be noted that rr_r is the utilization rate of raw materials for manufacturing products.

$$\sum_i ASM_{rijs} + \sum_{i'} ASBM_{ri'js} = \sum_k rr_r \cdot AMD_{jks} \quad \forall s, j, r \tag{4}$$

Constraint sets (5) and (6) show capacity constraints of the SPs and BSs. In these constraints, $\widetilde{SCap}_{ir}$ and $\widetilde{SBCap}_{i'r}$ are the capacity of the suppliers. On the other hand, σ_{is} is the rate of disruption.

$$\sum_j ASM_{rijs} \le (1 - \sigma_{is}) \cdot \widetilde{SCap}_{ir} \cdot YS_i \quad \forall i, s, r \tag{5}$$

$$\sum_j ASBM_{ri'js} \le \widetilde{SBCap}_{i'r} \cdot YSB_{i'} \quad \forall i', s, r \tag{6}$$

Equation (7) calculates the amount of product shipped from MCs to DCs.

$$\sum_j AMD_{jks} = \sum_d ADD_{kds} \quad \forall s, k \tag{7}$$

Relation (8) calculates the amount of product shipped to DPs and also the amount of shortage, where $\widetilde{Dem}_{ds}$ is the demand size.

$$\sum_k ADD_{kds} + SH_{ds} \ge \widetilde{Dem}_{ds} \quad \forall s, d \tag{8}$$

Constraint sets (9) and (10) show the capacity limitation of MCs and DCs. In these constraints, $\widetilde{MCap}_j$ and $\widetilde{DCap}_{kl}$ are the capacity parameters. On the other side, τ_{js} and ρ_{ks} are the rates of disruption.

$$\sum_k AMD_{jks} \le (1 - \tau_{js}) \cdot \left(\widetilde{MCap}_j + ECAP_{js} \right) \quad \forall s, j \tag{9}$$

$$\sum_d ADD_{kds} \le \sum_l (1 - \rho_{ks}) \cdot \widetilde{DCap}_{kl} \cdot YD_{kl} \quad \forall s, k \tag{10}$$

The amount of returned products from DPs to CCs is calculated by constraint (11). It should be noted that a_s shows the rate of return of the product.

$$\sum_c ADC_{dcs} = \sum_k a_s \cdot ADD_{kds} \quad \forall s, d \tag{11}$$

The amount of goods sent from CCs to RCs is calculated by constraint (12), where rt is the percentage of the repairable product.

$$\sum_t ACR_{cts} = \sum_d rt \cdot ADC_{dcs} \quad \forall s, c \tag{12}$$

Constraint (13) shows the quantity of goods sent from CCs to disposal centres.

$$\sum_b ACB_{cbs} = \sum_d (1 - rt) \cdot ADC_{dcs} \quad \forall s, c \tag{13}$$

Relations (14) and (15) are the capacity constraints of CCs and RCs. In these constraints, $\widetilde{CCap}_{cl}$ and $\widetilde{TCap}_{tlq}$ are the capacity parameters. On the other side, π_{cs} and μ_{ts} are the rates of disruption.

$$\sum_d ADC_{dcs} \le \sum_l (1 - \pi_{cs}) \cdot \widetilde{CCap}_{cl} \cdot YC_{cl} \quad \forall s, c \tag{14}$$

$$\sum_c ACR_{cts} \le \sum_{l,q} (1 - \mu_{ts}) \cdot \widetilde{TCap}_{tlq} \cdot YR_{tlq} \quad \forall s, t \tag{15}$$

Equations (16) and (17) show the amount of product sent from the repair centre to the second-hand market. It should be noted that $\widetilde{DR}_{gs}$ is the demand of second-hand market.

$$\sum_g ARG_{tgs} \le \sum_c ACR_{cts} \quad \forall s, t \tag{16}$$

$$\sum_t ARG_{tgs} + BB_{gs} \ge \widetilde{DR}_{gs} \quad \forall s, g \tag{17}$$

Relation (18) shows the service level constraint, in which α represents the service level.

$$\frac{\sum_{k,d,s} \cdot ADD_{kds}}{\sum_{d,s} \widetilde{Dem}_{ds}} \ge \alpha \tag{18}$$

Equation (19) is the carbon capacity-and-trade policy constraint, where $\widetilde{EmCap}$ is the allowable carbon emission capacity.

$$\begin{aligned}
&\sum_{j,k} \widetilde{Mei} \cdot AMD_{jks} + \sum_{c,t} \widetilde{Rei}_q \cdot ACR_{cts} \\
&\quad + \widetilde{Tei} \cdot \Bigg(\sum_{i,j,r} d_{ij} \cdot ASM_{rijs} + \sum_{i',j,r} d_{i'j} \cdot ASBM_{ri'js} + \sum_{j,k} d_{jk} \cdot AMD_{jks} \\
&\quad + \sum_{k,d} d_{kd} \cdot ADD_{kds} + \sum_{d,c} d_{dc} \cdot ADC_{dcs} + \sum_{c,t} d_{ct} \cdot ACR_{cts} \\
&\quad + \sum_{c,b} d_{cb} \cdot ACB_{cbs} + \sum_{b,g} d_{bg} \cdot ARG_{tgs} \Bigg) + SC_s \le \widetilde{EmCap} + PC_s \quad \forall s
\end{aligned} \tag{19}$$

Constraint sets (20)–(22) ensure that each facility only can be opened with one capacity level. Also, constraint (23) shows that a repairing centre only can be established with one technology.

$$\sum_l YD_{kl} \le 1 \quad \forall k \tag{20}$$

$$\sum_l YC_{cl} \le 1 \quad \forall c \tag{21}$$

$$\sum_l YR_{tlq} \le 1 \quad \forall t, q \tag{22}$$

$$\sum_q YR_{tlq} \le 1 \quad \forall t, l \tag{23}$$

Finally, the range of decision variables is shown in constraints (24) and (25).

$$YS_i, YSB_{i'}, YD_{kl}, YC_{cl}, YR_{tlq} \in \{0, 1\} \quad \forall i, k, l, c, t \tag{24}$$

$$\begin{aligned}
&ASM_{rijs}, ASBM_{ri'js}, AMD_{jks}, ADD_{kds}, ADC_{dcs}, ACR_{cts}, \\
&\quad ACB_{cbs}, ARG_{tgs}, \\
&\quad SH_{ds}, BB_{gs}, ECAP_{js}, PC_s, SC_s \ge 0 \quad \forall i, k, l, c, t.
\end{aligned} \tag{25}$$

3.4 Uncertainty modelling

Since the business environment is faced with severe fluctuations, one of the main issues in the field of SC management problem is uncertainty [25, 59, 60]. Ignoring the uncertainty may lead to achieving unrealistic solutions [34, 43]. Therefore, studying the research problem under uncertainty seems to be necessary. In general, researchers categorized the uncertainty into three main parts [2, 61, 62]: (I) randomness, (II) epistemic, (III) deep uncertainty. Randomness uncertainty is related to the condition in which there are enough historical data to estimate the distribution functions of the parameters. On the other side, epistemic uncertainty occurs when there is a lack of knowledge about historical data, and experts' opinion is needed to gather the required data (usually applying questionnaires and linguistic variables). Finally, deep uncertainty is related to a lack of information in the input data (interested readers refer to [2, 61] to see more about different types of the uncertainty). There are different methods to tackle each type of uncertainty shown in Fig. 3. In this research, to consider the high level of uncertainty and improve the system performance for tackling the uncertainty, we investigate the research problem under the mixed uncertainty (based on randomness and epistemic uncertainties). Considering this point not only brings the studied problem closer to real-world conditions but also leads to achieving more realistic solutions [63]. Therefore, the research problem is studied under mixed uncertainty in the present paper.

This section briefly defines the RPS approach applied in this study to tackle the mixed uncertainty. To better understand, we explain this method on the following compact model.

$$\begin{aligned}
&\text{Min} \;\; Z = \tilde{c} \cdot x + \sum_s p_s \cdot \tilde{f} \cdot y_s \\
&Ax \le \tilde{d} \\
&Ly_s \ge \tilde{h}_s \\
&x, y_s \ge 0
\end{aligned} \tag{26}$$

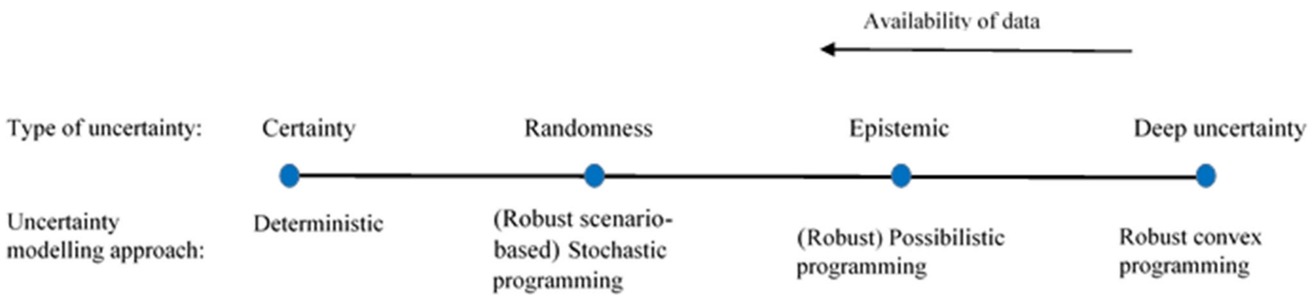


Fig. 3 Different types of uncertainties [2, 61]

In model (26), x and y_s are borders of the variables and occurrence probability of the scenarios; $\tilde{c}, \tilde{f}, \tilde{d}$, and $\tilde{h}_s$ are fuzzy parameters with triangular distribution (for example$\tilde{c} = (c^1, c^2, c^3)$). On the other hand, the constraint's coefficients are shown by L, h, and A. The RPS counterpart of the model (27) is written below:

$$\begin{aligned}
&\text{Min } Z = \left[\frac{c^1+c^2+c^3}{3}\right]\cdot x + \sum_s p_s \cdot \left[\frac{f^1+f^2+f^3}{3}\right].y_s \\
&\quad + \beta \sum_s p_s \cdot \left[\left(\left(\left[\frac{f^1+f^2+f^3}{3}\right]\cdot y_s \right.\right.\right. \\
&\quad \left.\left.\left. - \sum_{s'} p_{s'} \cdot \left[\frac{f^1+f^2+f^3}{3}\right]\cdot y_{s'}\right) + 2\theta_s\right]\right. + \sum_s \varphi \cdot \psi_s \\
&\quad Ax \leq (2\alpha - 1)\cdot d^1 + (2 - 2\alpha)\cdot d^2 \\
&\quad Ly_s + \psi_s \geq (2 - 2\vartheta)\cdot h_s^3 + (2\vartheta - 1)\cdot h_s^2 \\
&\quad \left[\frac{f^1+f^2+f^3}{3}\right]\cdot y_s - \sum_s p_s \cdot \left[\frac{f^1+f^2+f^3}{3}\right] \\
&\quad \cdot y_s + \theta_s \geq 0
\end{aligned} \tag{27}$$

In the above model, β represents the importance (weight) of the model robustness, δ the importance (weight) of the solution robustness, constraints satisfaction levels are shown by α, and ϑ. To read more about this method, interested readers can see [43, 63, 64]. The RPS counterpart is presented in Supplementary materials (Section A).

4 Solution methodology

In this study, to achieve the solution, there are two challenges. First, the problem is formulated by a multi-objective model; therefore, we need a multi-objective approach to convert the suggested model to a single one. Also, another challenge in solving the proposed model is the NP-hardness of the offered model. In this regard, to convert the MOMM to a single model, we apply the LP-metric method, which is one of the well-known methods to solve the MOMMs. Also, since the SC network configuration is considered as an Np-Hard problem [44–46], this research applies metaheuristic algorithms. To do this, we employ the simulated annealing algorithm (SA), genetic algorithm (GA), traditional particle swarm optimization (TPSO) and also develop an enhanced PSO (EPSO) algorithm to solve the research problem. In this section, we briefly describe each of mentioned algorithms and then explain the proposed EPSO. It should be noted that the way of combining the LP-metric method with the metaheuristic algorithms is explained in Supplementary materials (Section B).

Here, we explain the main reasons for employing the mentioned methods. The LP-metric method is a widely used approach to solve the multi-objective models, which has been applied in several previous studies to solve the multi-objective problems (for example, see [48, 65–68]) and showed good performance. Also, the calculation in this method is simple and implementation is easy. Hence, in this study, we select this approach to convert the suggested MOMM to a single one. On the other hand, the main reason for applying the SA, GA, and PSO algorithms is their easy implementation, simple concept, and quick convergence. On the other side, many studies in the field of supply chain applied the mentioned algorithms to solve the research problem (for example, see [6, 21, 63, 69–71]) and achieved the appropriate outputs that showed the good performance of the PSO algorithm to solve the supply chain problem. The methodology of the current study is shown in Fig. 4.

4.1 The LP-metric method

The LP-metric method is one of the widely used methods to solve the multi-objective models, which is more perceptible for executives compared to other methods, and in many cases of using this method, such as [48, 65–68, 72], acceptable results have been provided. In general, for the minimization objective function, the LP-metric method can be formulated as follows:

$$Z_{\text{total}} = \frac{w_1 \cdot (Z_1 - Z_1^{\min})}{Z_1^{\max} - Z_1^{\min}} + \frac{w_2 \cdot (Z_2 - Z_2^{\min})}{Z_2^{\max} - Z_2^{\min}} \tag{28}$$

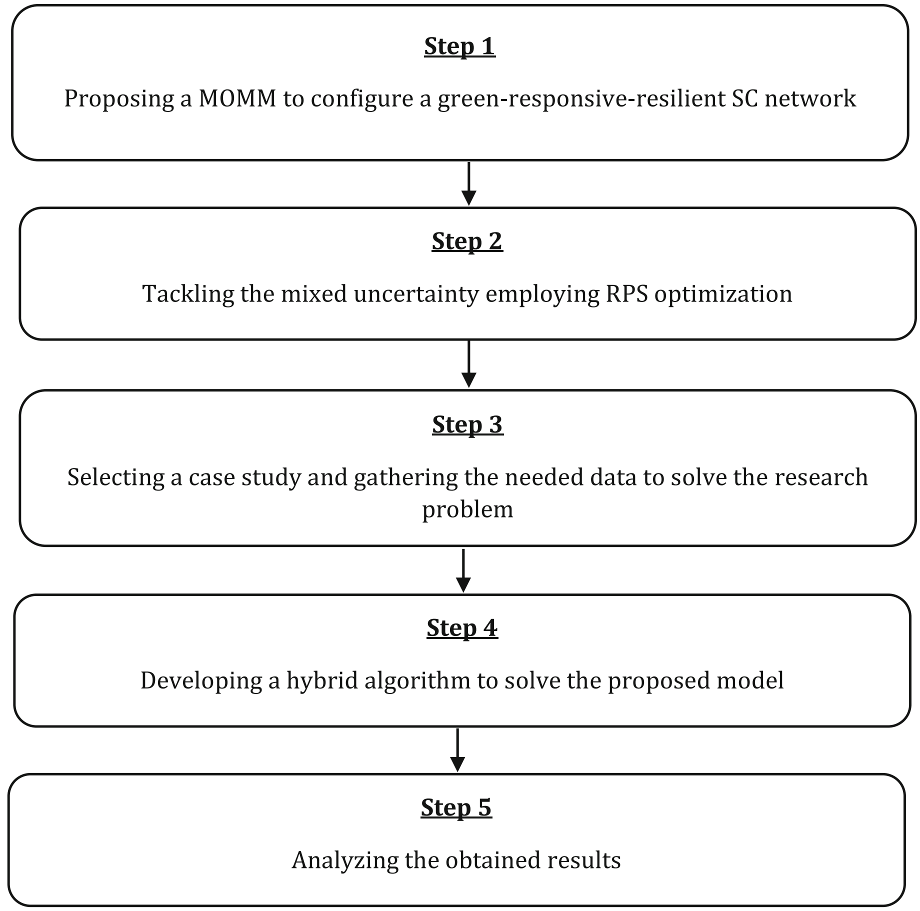


Fig. 4 The steps of conducting the present research

In the above equation, w_i shows the weight of the i th objective function (Zi). In other words, w_1 is the weight of the first objective function (OF) and w_2 represents the weight of the second OF ($w_1 + w_2 = 1$). To set the value of these parameters, in this study, we use the experts' opinions. However, these parameters can be obtained using some decision-making methods such as the Analytic Hierarchy Process (AHP) and the Best–Worst Method (BWM). Z_i^{max} and Z_i^{min}, respectively, denote the maximum and minimum values of the ith objective function.

4.2 SA

The SA developed by Kirkpatrick et al. [73] is one of the metaheuristic algorithms which is widely applied to solve hard combinatorial optimization problems [72]. The SA is a single-based metaheuristic algorithm, and the nature of this method is based on the annealing process of solids. In this method, first, the initial solution is created and then the objective function of this solution is measured. Afterwards, to improve the initial solution, a neighbourhood solution is created by utilizing some operators.

4.2.1 Solution representation

In this study, we apply a two-stage called the random key (RK) method. This method helps the researchers to handle their problems with different algorithms and operators [74]. The mentioned method has phases. At the outset, a solution is generated by random numbers and then it is converted to a feasible discrete solution by a procedure [75]. In this study, the solution is generated based on two sub-solutions that are depicted in Fig. 5. In the first sub-solution, a matrix is created by $Uniform(0, 1)$ (see Fig. 5a). This sub-solution is used for binary variables such as PSs, BSs, DCs, and CCs. On the other hand, the second sub-solution (Fig. 5b) determines the flow of materials in the SC network. Then, the columns of the second matrix are normalized to specify how a facility supplies its demands from another facility (for example, how MCs purchase the raw material between the different elected SPs). To better understand, in Fig. 5a, suppliers 2, 4, and 5 have been selected to supply the needed raw materials (i.e. $YS_2 = YS_4 = YS_5 = 1$). On the other side, as can be seen in Fig. 5b, supplier 2 supplies manufacturers 1 & 4, supplier 4 supplies manufacturer 3, and supplier 5 supplies manufacturers 2 & 3. Regarding the quantity of raw materials shipped from suppliers to

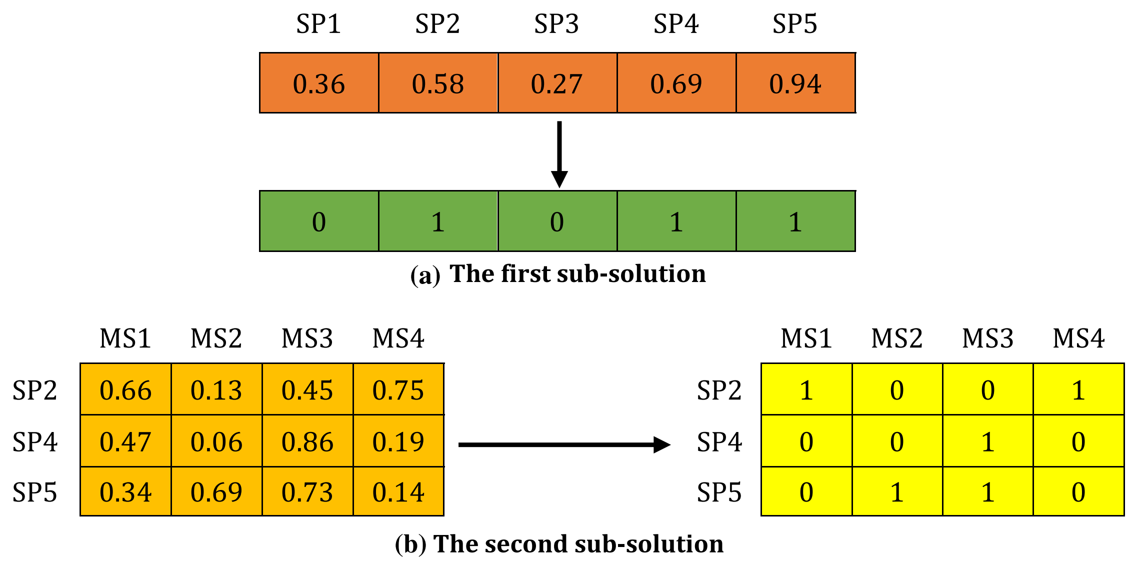
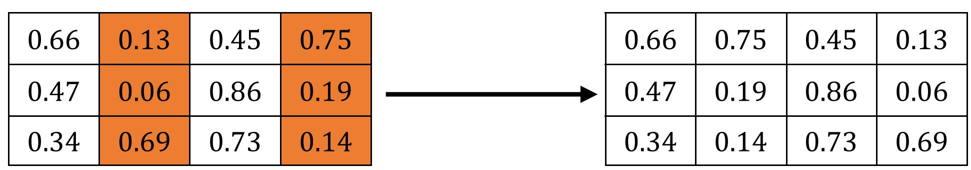


Fig. 5 The schematic of the solution with two parts in a two-stage RK method

Fig. 6 The procedure of creating the neighbour solution



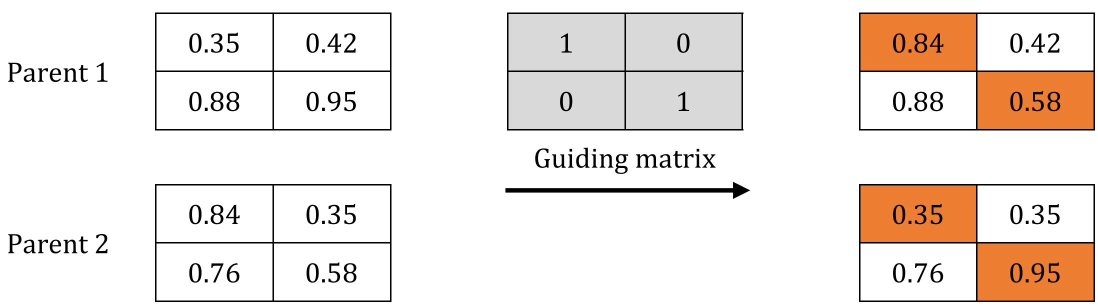


Fig. 7 The crossover operator

manufacturers, if a manufacturer has been allocated to a supplier, this supplier should meet the demand of this manufacturer. For example, suppose that the demand of manufacturer 1 is equal to 100. Since manufacturer 1 is allocated to supplier 2, this supplier sends 100-unit raw materials to this manufacturer. Also, if the supplier could not satisfy all demands of a manufacturer, this manufacturer purchases its need from other suppliers. See [74] and [75] to read more details.

4.2.2 Creating neighbour solution

In this research, to create a neighbour solution, we have applied a procedure that is illustrated in Fig. 6. Based on this procedure, two columns are randomly chosen and the elements of these columns are swapped. It should be noted that this operator is also employed in other previous papers such as [74] and [75].

4.3 GA

The GA algorithm is one of the methods to solve complex optimization problems [76, 77]. In this algorithm, at the

Fig. 8 The pseudo-code of the proposed enhanced PSO

```
Inputs:
MaxIt (Maximum number of iterations), SS (Swarm-size), c1 , c2, χ (Constriction coefficient)
Create an initial swarm

While t< MaxIt:
    For k=1 to SS:

        For each particle k, the OF is calculated
        The best positions are evaluated and updated.
        For each particle, the velocity and position are updated.
        For each particle, the OF is calculated.
        The personal best position is updated:

          If F_k^t < F_k^pbest:
               Pbest_k(t)=x_k(t)

        The global best position is updated

               If F_k^pbest < F^gbest:
                 Gbest= Pbest(t)
              endif
        For each particle, the velocity and position are updated
        The local search is performed
        For each particle, the OF is calculated:
        The personal best position is updated:
                 If F_k^t < F_k^pbest:
                          Pbest_k(t)=x_k(t)
                     else
                   If random < exp{-(f(t)-f(pbest))/T} then
                          Pbest_k(t)=x_k(t)
                   Endif
                 Endif
          The global best position is updated:
               If F_k^pbest < F^gbest:
                 F^gbest = F_k^pbest
                 gbest= pbest(t)
              Endif
    Endfor
The local search is performed on Gbest solution.
The particle with the best OF is considered as Gbest
t = t + 1
T = α.T
Endwhile
```

outset, a population of chromosomes is randomly generated as solutions. Then, the fitness function is calculated for each chromosome. Afterwards, by applying some operators (i.e. crossover and mutation), the solutions are improved [63]. In this research, the chromosome of the GA is exactly similar to the solution representation of the SA algorithm. Also, the mutation operator of the GA is the same as the way of creating a neighbour solution in the SA. So, in this section, we briefly describe the crossover operator.

Table 2 Obtaining the ideal solution for each objective function

Population (swarm) number	First objective function	Second objective function
$P1$ ($S1$)	f_{11}	f_{21}
$P2$ ($S2$)	f_{12}	f_{22}
$P3$ ($S3$)	f_{13}	f_{23}
…	…	…
Pn (Sn)	f_{1n}	f_{2n}
$fmin$	$f_{1\min}$	$f_{2\min}$

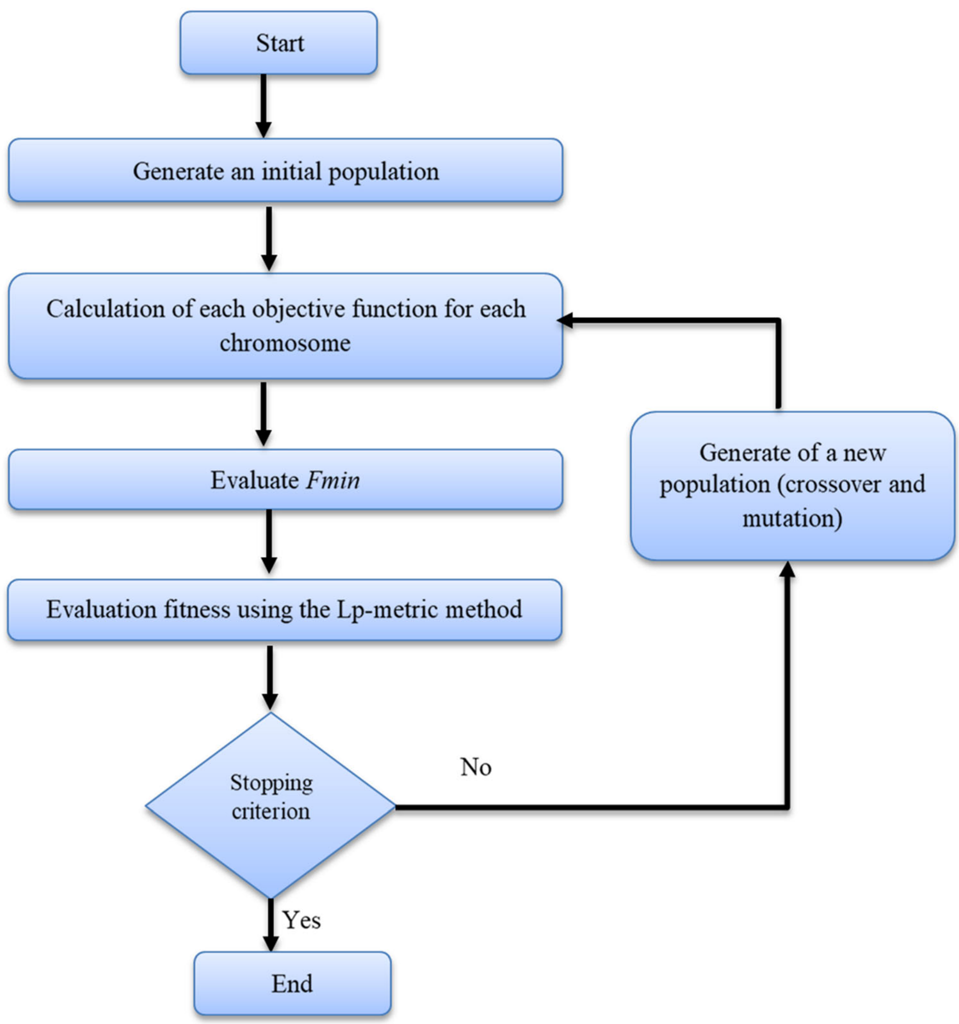


Fig. 9 The way of combining the LP-metric method and the GA

4.3.1 Roulette wheels to select parents

Parent selection is a process of choosing chromosomes (parents) from the population for reproducing the next generations. Actually, selecting individuals within the population for mating purposes is the main goal of the selection process. In this study, the roulette wheel selection has been employed. In this approach, the chromosomes in each generation are sorted based on their corresponding fitness values. This is a widely used method to select parents applied in many previous studies (see [78–82]).

4.3.2 Crossover

Crossover may be the most significant phase in a genetic algorithm. For each pair of parents to be mated, a crossover point is randomly chosen from within the genes. In this research, similar to Rahimi et al. [21], we have employed the guiding matrix to design the crossover operator. This is a matrix with binary elements. At first, two parent are selected using the roulette wheel method and then the guiding matrix is formed due to the size of the parents (solutions). Now, to create new solutions (offspring), if the

Fig. 10 The selected product (oxygen concentrator)

Fig. 11 A general schematic of current SC network of the considered case study

Table 3 Names and probability of occurrence of scenarios

Scenario	Description	Probability of occurrence
pcod	Pessimistic DCR and Optimistic D	0.05
mcod	Most likely DCR and Optimistic D	0.15
ocod	Optimistic DCR and Optimistic D	0.05
pcmd	Pessimistic DCR and Most likely D	0.1
mcmd	Most likely DCR and Most likely D	0.3
ocmd	Optimistic DCR and Most likely D	0.1
pcpd	Pessimistic DCR and Pessimistic D	0.05
mcpd	Most likely DCR and Pessimistic D	0.15
ocpd	Optimistic DCR and Pessimistic D	0.05

value of the element of the guiding matrix is equal to one, the corresponding element in the parents is changed; otherwise, the elements remain unchanged. Figure 7 demonstrates an example of the procedure of the proposed crossover operator. See [21] to read more about this type of crossover operator.

4.4 TPSO

A well-known population-based algorithm is the PSO algorithm that solves continuous optimization problems [83–85]. This algorithm considers the solutions as a particle and the population as the swarm. In this method, the velocity and position vectors are updated according to the following equations.

$$X_i(k+1) = X_i(k) + v_i(k+1) \tag{29}$$

$$v_i(k+1) = w \cdot v_i(k) + c_1 \cdot r_1 \cdot (Pbest_i - X_i(k)) + c_1 \cdot r_1 \cdot (Gbest - X_i(k)) \tag{30}$$

The velocity and position vectors of particle i in iteration k are defined by $v_i(k)$ and $X_i(k)$, respectively. The best position of particle i is determined by $pbest_i$, and the best position vector in the population is determined by $gbest$. The inertia weight is shown by w and acceleration coefficients are c_1 and c_2. Two random numbers, r_1 and r_2, generated in the interval [0 1]. It should be noted that the structure of the solution for the PSO algorithm is similar to the SA and GA algorithms.

Table 4 Values of the scenario-based parameters

Scenario name	DCRs $(\sigma_{is}, \tau_{js}, \rho_{ks}, \pi_{cs}, \mu_{ts})$	$\widetilde{Dem}_{ds}$			$\widetilde{DR}_{gs}$		
		$\theta_{(1)}$	$\theta_{(2)}$	$\theta_{(3)}$	$\theta_{(1)}$	$\theta_{(2)}$	$\theta_{(3)}$
pcod	0.35	U[500 750]	U[750 1000]	U[1000 1250]	U[200 250]	U[250 300]	U[300 350]
mcod	0.2	U[500 750]	U[750 1000]	U[1000 1250]	U[200 250]	U[250 300]	U[300 350]
ocod	0.05	U[500 750]	U[750 1000]	U[1000 1250]	U[200 250]	U[250 300]	U[300 350]
pcmd	0.35	U[450 600]	U[600 750]	U[750 900]	U[120 200]	U[200 280]	U[280 350]
mcmd	0.2	U[450 600]	U[600 750]	U[750 900]	U[120 200]	U[200 280]	U[280 350]
ocmd	0.05	U[450 600]	U[600 750]	U[750 900]	U[120 200]	U[200 280]	U[280 350]
pcpd	0.35	U[300 400]	U[400 500]	U[500 600]	U[80 120]	U[120 160]	U[160 200]
mcpd	0.2	U[300 400]	U[400 500]	U[500 600]	U[80 120]	U[120 160]	U[160 200]
ocpd	0.05	U[300 400]	U[400 500]	U[500 600]	U[80 120]	U[120 160]	U[160 200]

Table 5 The level of the parameters for Taguchi experiments

Algorithm	Parameter	Level		
		1	2	3
GA	*MaxIt*	300	350	400
	Npop	55	65	75
	Pc	0.6	0.7	0.8
	Pm	0.1	0.2	0.3
SA	*MaxIt*	300	350	400
	T	35	40	45
	Alpha	0.9	0.95	0.99
TPSO	*MaxIt*	300	350	400
	Swam − Size	55	65	75
	*c*1	2	2.1	2.2
	*c*2	2	2.1	2.2
EPSO	*MaxIt*	300	350	400
	Swam − Size	55	65	75
	*c*1	2	2.1	2.2
	*c*2	2	2.1	2.2
	T	35	40	45
	Alpha	0.9	0.95	0.99

4.5 EPSO

In this study, to improve the performance of the PSO algorithm, we try to modify this algorithm by adding the three following features:

1. *Local search* For improving the performance of the PSO algorithm, a local search operator similar to the mutation operator of the genetic algorithm has been added to this algorithm.
2. *Boltzmann function* We have added the Boltzmann function from the SA algorithm to the PSO algorithm that leads to improving the exploitation of the algorithm by randomly returning some of the solutions with a worse OF to the algorithm's loop.
3. *Adding constriction coefficient* (χ) Based on Clerc and Kennedy [86] and Poli [87], incorporating multiplier χ into the PSO algorithm can accelerate the convergence process and enhance the overall performance of the PSO algorithm. Considering Eq. (31), the appropriate value of χ will be calculated by Eq. (32) [78]:

$$c_1 + c_2 > 4 \tag{31}$$

$$\chi = \frac{2}{C - 2 + \sqrt{C^2 - 4C}}, \quad (C = c_1 + c_2) \tag{32}$$

It should mathematical proof of the above relations was provided in Clerc and Kennedy [86]. Considering the multiplier χ, the velocity vector in relation (30) is converted to relation (33) as follows [78]:

$$\begin{aligned} v_i(k+1) = \chi \cdot (w.v_i(k) + c_1 \cdot r_1 \\ \cdot (Pbest_i - X_i(k)) + c_1 \cdot r_1 \cdot (Gbest - X_i(k))) \end{aligned} \tag{33}$$

The pseudo-code of the proposed enhanced PSO is depicted in Fig. 8.

4.6 Combining the LP-metric method and metaheuristic algorithms

As mentioned, this research attempts to employ the combination of the LP-metric method and metaheuristic algorithms to solve the suggested multi-objective model. In this section, we provide some explanations in this regard. At the outset, the values of the ideal solutions are calculated according to the manner provided in Table 2. For this purpose, for each population (swarm), the values of both

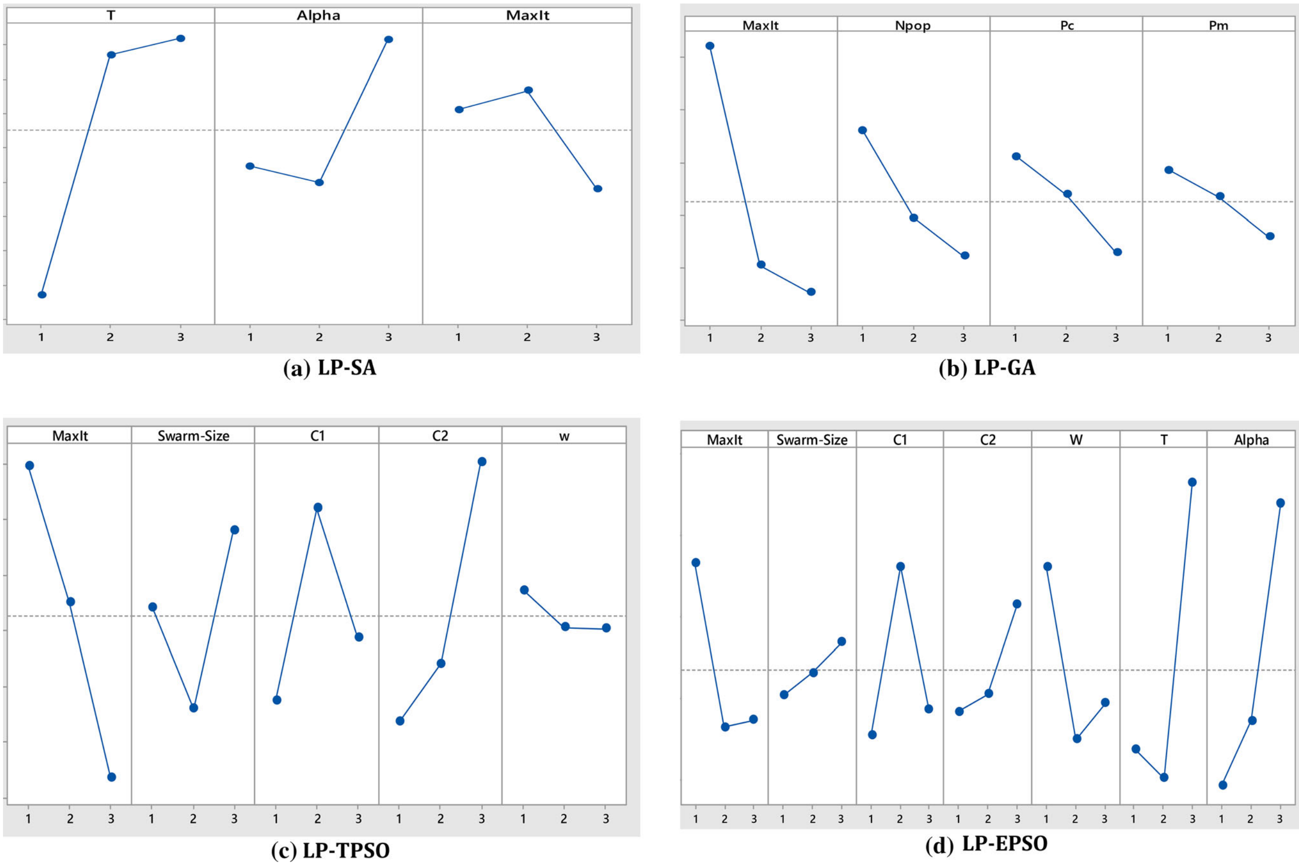


Fig. 12 The S/N ratio charts for the proposed algorithms

OFs are measured. In this part, f_{1i} and f_{2i}, respectively, denote the value of the first and second OFs. Afterwards, the ideal solution, which is the best value of each OF in a population (swarm), is applied to GA and PSO algorithms as the fitness value obtained by the LP-metric method. To better understand, see Fig. 9, which depicts the chart of the hybrid LP-GA algorithm. It should be noted that the same way is applied to the SA algorithm but by considering a single solution rather than a population.

5 Case study

In this section, the case study, parameters setting, the obtained results from solving the model, and sensitivity analysis are presented.

According to World Health Organization (WHO) report, MDs are known as one of the most important parts of the healthcare system. The critical role of MDs in ensuring the quality of life across the world is completely shown in the recent pandemic (COVID-19). The literature showed that the supply chain of these goods has been rarely addressed by the researchers. In this research, we have attempted to investigate a case study to show the efficiency of the offered model and the performance of the developed algorithms. In this regard, given the crucial role of MDs, especially in the Coronavirus disease, this study selected the MDs industry as a case study (a company located in Mazandaran province, Iran). One of the devices that its demand increases during Coronavirus disease, is oxygen concentrators. The oxygen concentrator is one of the widely used MDs that provide the oxygen needed by patients (patients with low oxygen levels) by constantly concentrating ambient air into pure oxygen. The selected product and its component are shown in Fig. 10.

Increasing environmental concerns, some government regulations, and international obligations require this company to incorporate green factors in its SC network. On the other side, this firm is interested in increasing the resiliency and responsiveness of its SC network to obtain a competitive advantage and increase its market share. Hence, we have tried to design a responsive-resilient SC network considering environmental issues for this company. Figure 11 illustrates a general schematic from the location of MCs and customers of this firm. The way of generating scenarios and data on the scenario-based parameters is given in Tables 3 and 4. Because of the space limitation, the related data (scenarios and values of the

Table 6 The results of the small-sized problems

Problem	LP-metric (exact)					LP-SA							LP-GA						
	$Z1^* \times 10^3$	$Z2^*$	$Z1 \times 10^3$	Z2	CPUT (s)	$Z1^* \times 10^3$	$Z2^*$	$Z1 \times 10^3$	PRE1	Z2	PRE2	CPUT (s)	$Z1^* \times 10^3$	$Z2^*$	$Z1 \times 10^3$	PRE1	Z2	PRE2	CPUT (s)
1	56,872.8	124.8	56,872.8	124.8	13.2	56,872.8	124.8	56,872.8	0	124.8	0	18.3	56,872.8	124.8	56,872.8	0	124.8	0	38.3
2	64,156.1	129.7	64,156.1	129.7	24.5	64,156.1	129.7	64,156.1	0	129.7	0	21.8	64,156.1	129.7	64,156.1	0	129.7	0	41.5
3	75,654.9	133.3	76,380.5	134.5	59.9	76,078.5	133.8	76,808.2	0.56	135.0	0.38	25.1	75,654.9	133.3	76,380.5	0	134.5	0	48.2
4	91,232.4	140.6	92,107.4	141.9	95.6	92,327.2	141.9	93,212.7	1.2	143.2	0.95	28.2	92,035.2	141.6	92,917.9	0.88	142.9	0.67	55.6
5	101,346.2	163.8	102,318.2	165.3	236.1	103,170.4	165.9	104,159.9	1.8	167.4	1.3	31.5	102,562.3	165.4	103,546.0	1.2	166.9	0.95	60.2
6	113,772.3	188.0	114,863.5	189.7	516.4	116,502.8	191.4	117,620.2	2.4	193.1	1.8	35.6	115,706.4	190.7	116,816.2	1.7	192.4	1.4	67.8
7	135,974.3	203.6	137,625.8	206.5	864.5	138,965.8	206.9	140,653.6	2.2	209.8	1.6	41.3	138,013.9	205.9	139,690.2	1.5	208.8	1.1	71.2
8	162,851.2	234.9	164,829.2	238.2	1538.3	167,411.1	239.3	169,444.4	2.8	242.7	1.9	46.2	166,271.1	238.6	168,290.6	2.1	242.0	1.6	79.6
9	185,286.3	275.7	187,536.7	279.6	3462.8	191,400.7	282.3	193,725.4	3.3	286.3	2.4	52.8	190,474.2	281.5	192,787.7	2.8	285.5	2.1	85.4
10	213,352.8	305.8	215,944.1	310.1	7351.2	219,966.7	312.5	222,638.4	3.1	316.9	2.2	58.5	218,686.6	311.6	221,342.7	2.5	316.0	1.9	91.3
11	253,741.6	341.0	256,823.5	345.8	12,736.5	262,876.3	350.1	266,069.1	3.6	355.1	2.7	66.1	261,607.6	348.8	264,785.0	3.1	353.8	2.3	100.6
12	310,498.0	386.0	314,269.2	391.5	18,163.1	322,607.4	397.9	326,525.7	3.9	403.6	3.1	75.4	321,675.9	396.9	325,582.9	3.6	402.5	2.8	115.8
13	355,113.6	409.4	359,426.7	415.2	23,085.6	368,252.8	420.8	372,725.5	3.7	426.8	2.8	84.2	366,832.3	419.6	371,287.8	3.3	425.6	2.5	126.3
14	396,754.6	440.4	401,573.5	446.7	29,175.3	412,624.8	454.5	417,636.4	4	461.0	3.2	91.6	410,641.1	453.3	415,628.6	3.5	459.7	2.9	132.1
15	443,979.8	490.5	449,372.3	497.5	36,669.5	462,626.9	507.7	468,245.9	4.2	514.9	3.5	99.1	460,851.0	506.2	466,448.4	3.8	513.4	3.2	141.5

Problem	LP-TPSO							LP-EPSO						
	$Z1^* \times 10^3$	$Z2^*$	$Z1 \times 10^3$	PRE1	Z2	PRE2	CPUT (s)	$Z1^* \times 10^3$	$Z2^*$	$Z1 \times 10^3$	PRE1	Z2	PRE2	CPUT (s)
1	56,872.8	124.8	56,872.8	0	124.8	0	33.3	56,872.8	124.8	56,872.8	0	124.8	0	40.6
2	64,156.1	129.7	64,156.1	0	129.7	0	36.1	64,156.1	129.7	64,156.1	0	129.7	0	44.0
3	76,267.7	134.0	76,999.2	0.81	135.2	0.52	41.9	75,654.9	133.3	76,380.5	0	134.5	0	51.1
4	92,874.5	142.2	93,765.3	1.8	143.5	1.1	48.4	91,232.4	140.6	92,107.4	0	141.9	0	58.9
5	103,474.5	166.1	104,466.9	2.1	167.6	1.4	52.4	102,207.6	164.9	103,187.9	0.85	166.4	0.68	63.8
6	116,957.9	191.6	118,079.7	2.8	193.3	1.9	59.0	115,478.9	190.1	116,586.5	1.5	191.8	1.1	71.9
7	139,373.6	206.9	141,066.4	2.5	209.8	1.6	61.9	137,606.0	205.5	139,277.3	1.2	208.4	0.93	75.5
8	167,573.9	239.1	169,609.2	2.9	242.5	1.8	69.3	165,945.5	238.1	167,961.0	1.9	241.5	1.4	84.4
9	191,771.3	282.9	194,100.5	3.5	286.9	2.6	74.3	189,547.8	280.4	191,850.0	2.3	284.4	1.7	90.5
10	220,180.0	312.8	222,854.3	3.2	317.2	2.3	79.4	217,833.2	310.0	220,478.9	2.1	314.4	1.4	96.8
11	263,130.1	350.5	266,326.0	3.7	355.5	2.8	87.5	260,085.2	347.5	263,244.1	2.5	352.4	1.9	106.6
12	322,917.9	397.9	326,840.0	4	403.6	3.1	100.7	319,502.4	394.5	323,383.0	2.9	400.1	2.2	122.7
13	368,607.9	421.2	373,084.9	3.8	427.2	2.9	109.9	364,701.6	417.6	369,131.2	2.7	423.5	2	133.9
14	413,418.3	454.9	418,439.6	4.2	461.4	3.3	114.9	409,054.0	451.5	414,022.3	3.1	457.9	2.5	140.3
15	463,959.0	508.7	469,594.1	4.5	515.9	3.7	123.1	458,631.2	504.7	464,201.6	3.3	511.9	2.9	150.0

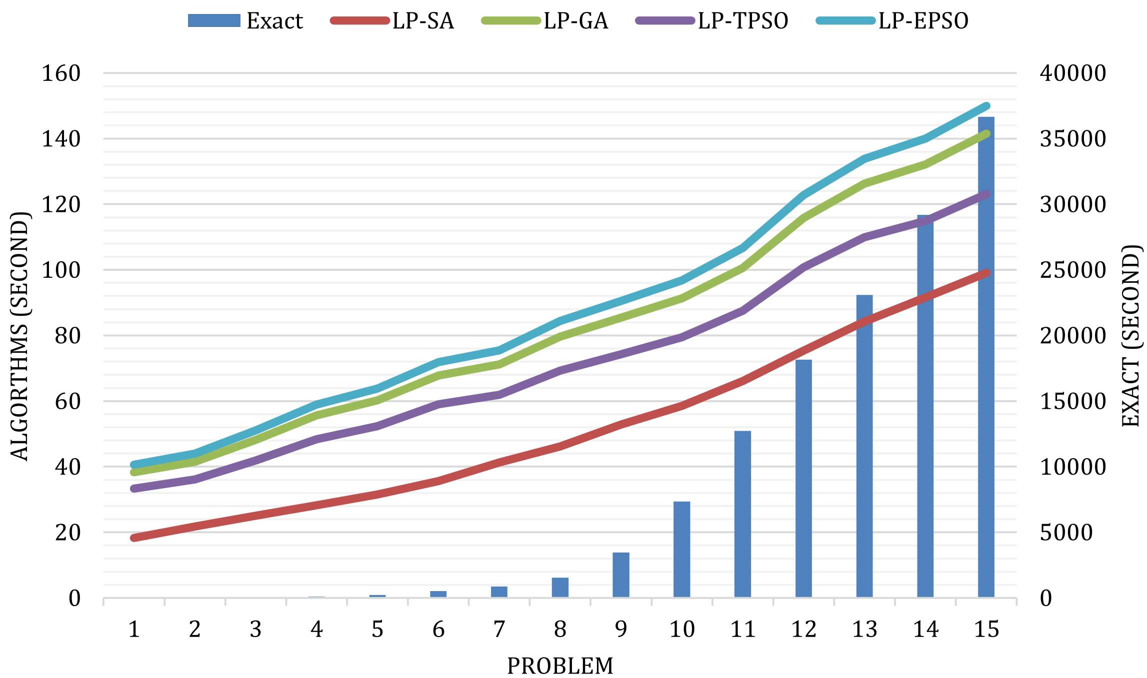


Fig. 13 The performance of the algorithms based on the CPU time metric

parameters) are given in Supplementary Materials (Section C).

In this research, we define three main scenarios (pessimistic, most likely, and optimistic) and then consider the combination of these scenarios in order to generate values of the Demands (D) and Disrupted Capacity Rate (DCR) parameters. The combination of scenarios is given in Table 3. Accordingly, the values of demand and DCR parameters are presented in Table 4.

5.1 Parameters setting

In this section, the parameters of the proposed algorithms are tuned. To do this, we have applied the Taguchi method as one of the widely used approaches to setting the parameters of the metaheuristic algorithms. Due to the limitation of the space, we do not describe this method, and the interested readers can see [78, 88–90] for more study. Table 5 shows the algorithms' parameters and their level for conducting Taguchi experiments. It should be noted that we selected some candidate values for parameters based on the literature (e.g. [1–4]) and then chosen three ones according to trial and error. Also, Fig. 12 illustrates the signal-to-noise (S/N) ratio chart for each algorithm. It should be noted that, in the Taguchi method, the highest level of S/N ratio shows the best level of the parameter. For example, according to Fig. 12, for the LP-SA algorithm, the best value for the T parameter is the third level.

5.2 Results and discussion

To solve the research problem by the algorithms, we have designed 15 small-sized instances and 15 large-sized instances. The obtained results for the small-sized instances are reported in Table 6. To examine the performance of the developed algorithms, we consider two measures: (1) the quality of solutions and (2) CPU time. It should be noted that CPU time is one of the critical metrics to compare the performance of the metaheuristic algorithms, which have been widely used in previous studies (see [21, 48, 63, 68, 88, 91, 92]). Since in small-sized instances, the global optimal solution is available, we apply the percentage relative error (PRE) to assess the quality of the obtained solutions. This measure is calculated based on the following relation.

$$\mathrm{PRE} = \frac{A_{\mathrm{sol}} - E_{\mathrm{sol}}}{E_{\mathrm{sol}}} \times 100 \tag{34}$$

where A_{sol} shows the solution obtained by the algorithm and E_{sol} denotes the solution obtained by the exact method. It should be noted that we run each test problem 10 times and report the best solution obtained by the algorithms in Table 6. It should be noted that the algorithms are implemented in the MATLAB 16.0 software on an Intel CORE i5 2.67 GHz PC with RAM 8. As shown in Table 6, the developed algorithms can achieve high-quality solutions in better CPU time than the exact method. In solutions' quality criteria, the developed LP-EPSO has the best performance among algorithms with the average PRE

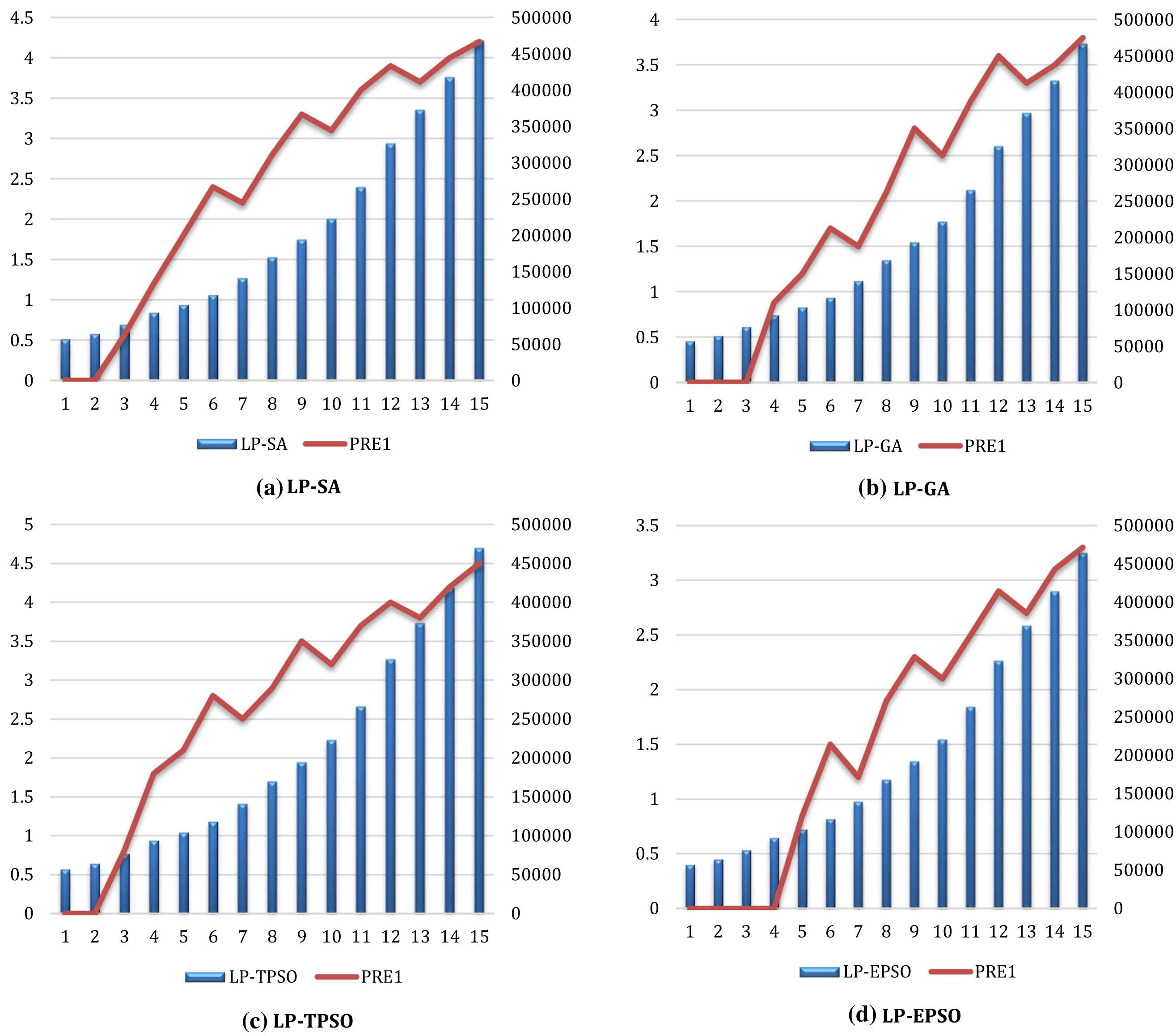


Fig. 14 Comparing the algorithms based on the PRE metric

($\overline{PRE} = \frac{\overline{PRE1}+\overline{PRE2}}{2}$) equal to 1.24. On the other hand, the LP-SA algorithm has better performance than the other algorithms according to CPU time criteria. To better understand, Figs. 13 and 14 illustrate the performance of the developed algorithms in terms of CPU time and solutions' quality. It should be noted that although we have solved the research problem using Eq. (28), the value of each OF (Z1 and Z2) can easily obtain from the software. In this regard, we defined two variables (e.g. ZZ1 and ZZ2), in which ZZ1 is equal to the formulation of the first OF and ZZ2 is equal to the formulation of the second OF. After solving the problem with objective function Z (Eq. 28), the software calculates the values of the two mentioned variables. So, the value of ZZ1 is equal to the final value for the first OF and the value of ZZ2 demonstrates the final value for the second OF. It should be noted that to achieve Z_i^* (PIS = Positive Ideal Solution), the problem is solved only with *i*th objective function and the obtained result is equal to Z_i^*. Indeed, in Table 6, Z_1^* is the positive ideal solution for the first OF and Z_1 shows the obtained value for the first OF in the LP-metric method, which may have a distance from the PIS because in the LP-metric model, both OFs are considered. On the other side, Z_2^* represents the PIS for the second OF, but Z_2 denotes the value of the second OF achieved by the LP-metric approach.

Also, the outputs for the large-sized instances are given in Table 7. In this section, since the exact method could not solve the problems in a reasonable time, the global optimal solution is not available. Hence, we use the relative

Table 7 The results of solving large-sized instances

Problem	LP-SA					LP-GA					LP-TPSO					LP-EPSO				
	Z1 $\times 10^3$	RPD1	Z2	RPD2	CPUT	Z1 $\times 10^3$	RPD1	Z2	RPD2	CPUT	Z1 $\times 10^3$	RPD1	Z2	RPD2	CPUT	Z1 $\times 10^3$	RPD1	Z2	RPD2	CPUT
1	771,130.2	1.8	632.8	1.2	141.8	768,857.7	1.5	631.6	1	186.3	771,130.2	1.8	632.8	1.2	182.3	757,495.3	0	625.3	0	198.2
2	8,536,303.8	2.1	641.6	1.6	150.5	8,502,860.9	1.7	639.7	1.3	205.5	8,544,664.5	2.2	641.6	1.6	201.1	8,360,728.5	0	631.5	0	218.6
3	922,889.8	1.9	647.6	1.4	159.3	920,172.7	1.6	645.7	1.1	223.2	923,795.4	2	648.3	1.5	218.4	905,681.8	0	638.7	0	237.4
4	999,711.6	2.5	656.6	1.7	168.6	994,835.0	2	655.9	1.6	238.6	999,711.6	2.5	656.6	1.7	233.5	975,328.4	0	645.6	0	253.8
5	1,066,543.3	2.9	664.2	2	179.7	1,060,324.4	2.3	662.9	1.8	256.2	1,065,506.8	2.8	663.6	1.9	250.7	1,036,485.2	0	651.2	0	272.5
6	1,140,310.1	3.2	674.7	2.4	188.1	1,133,680.3	2.6	672.7	2.1	276.6	1,141,415.0	3.3	675.4	2.5	270.8	1,104,951.6	0	658.9	0	294.3
7	1,219,152.0	3	679.1	2.2	197.5	1,213,233.8	2.5	677.1	1.9	299.6	1,221,519.3	3.2	680.4	2.4	293.2	1,183,642.7	0	664.5	0	318.7
8	1,303,463.3	3.6	688.9	2.5	208.2	1,295,914.3	3	687.6	2.3	314.4	1,303,463.3	3.6	688.9	2.5	307.7	1,258,169.2	0	672.1	0	334.5
9	1,355,258.6	3.9	698.7	2.7	217.5	1,346,127.9	3.2	698.7	2.7	331.6	1,357,867.4	4.1	700.0	2.9	324.6	1,304,387.5	0	680.3	0	352.8
10	1,434,123.6	3.7	705.5	2.6	226.7	1,425,825.9	3.1	704.8	2.5	351.8	1,435,506.6	3.8	706.2	2.7	344.4	1,382,954.3	0	687.6	0	374.3
11	1,506,133.1	4.1	715.7	2.9	237.2	1,497,452.2	3.5	716.4	3	367.6	1,509,026.7	4.3	716.4	3	359.8	1,446,813.7	0	695.5	0	391.1
12	1,588,143.5	4.5	725.2	3.2	246.9	1,579,024.9	3.9	725.9	3.3	384.0	1,588,143.5	4.5	725.2	3.2	375.8	1,519,754.5	0	702.7	0	408.5
13	1,676,948.0	4.9	737.7	3.7	257.1	1,665,757.7	4.2	737.0	3.6	397.2	1,680,145.2	5.1	739.1	3.9	388.8	1,598,615.8	0	711.4	0	422.6
14	1,751,597.8	4.7	744.8	3.5	268.5	1,741,560.0	4.1	744.1	3.4	412.8	1,754,943.7	4.9	745.5	3.6	404.0	1,672,968.3	0	719.6	0	439.1
15	1,859,300.1	5.2	760.0	4.1	277.8	1,850,463.1	4.7	757.8	3.8	425.4	1,862,834.9	5.4	761.5	4.3	416.3	1,767,395.5	0	730.1	0	452.5

percentage deviation (RPD) measure to compare the performance of the algorithms in terms of solutions' quality. The RPD is measured based on the following equation.

$$\mathrm{RPD} = \frac{A_{\mathrm{sol}} - B_{\mathrm{sol}}}{B_{\mathrm{sol}}} \times 100 \tag{35}$$

where B_{sol} represents the best solution among all of the algorithms. As shown in Table 7, the LP-EPSO method has the best performance according to the RPD metric (solutions' quality) and the LP-SA algorithm has the best performance according to the CPU time metric. Figure 15 compares the developed algorithms according to the CPU time metric. On the other side, to validate the obtained results, the means plot and least significant difference (LSD) interval (at 95% confidence level) for the $\overline{\mathrm{RPD}} = \frac{\mathrm{RPD1} + \mathrm{RPD2}}{2}$ value is conducted and depicted in Fig. 16. According to this figure, the LP-EPSO algorithm significantly has a better performance based on the solutions' quality metric.

5.3 Discussing the performance of the algorithms

In this section, a discussion about the performance of the metaheuristic algorithms is provided. According to the achieved results, in both small-sized and large-sized test problems, based on the solutions quality metric (i.e. PRE and RPD), the proposed EPSO has the best performance among all algorithms. To better understand, Table 8 and Fig. 17 compare the average value of the PRE metric for the employed algorithms. The main reason that leads to the proposed EPSO outperforming the other algorithms is that this algorithm has advantages over all of them, concurrently. In this regard, adding the local search operator, Boltzmann function, and constriction coefficient have led to significant improvement in exploration and exploitation processes in the proposed EPSO. In other words, by employing the local search and the Boltzmann function, we get rid of some drawbacks of the TPSO algorithm, such as weakness in exploring new solutions (i.e. improving the current solutions to better ones), which leads to a significant improvement in the performance of this algorithm. On the other side, using the constriction coefficient has a significant positive effect on the algorithm's better convergence and performance.

5.4 Sensitivity analysis

5.4.1 Demand

In order to investigate the behaviour of the proposed model according to demand changes, the problem has been solved

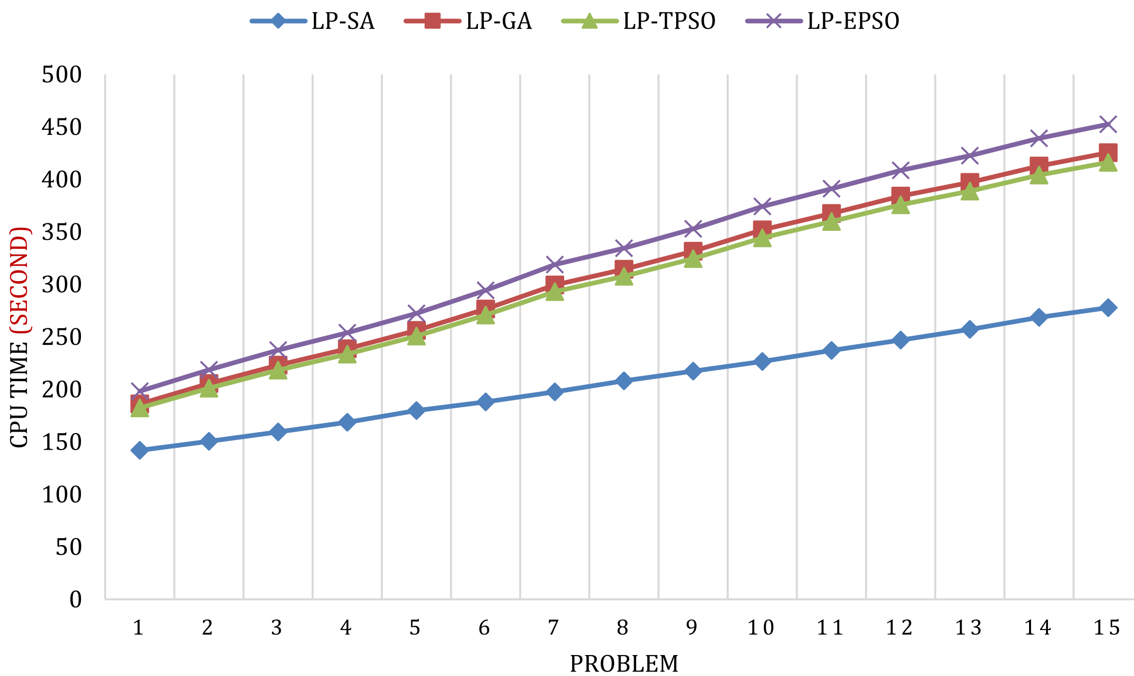
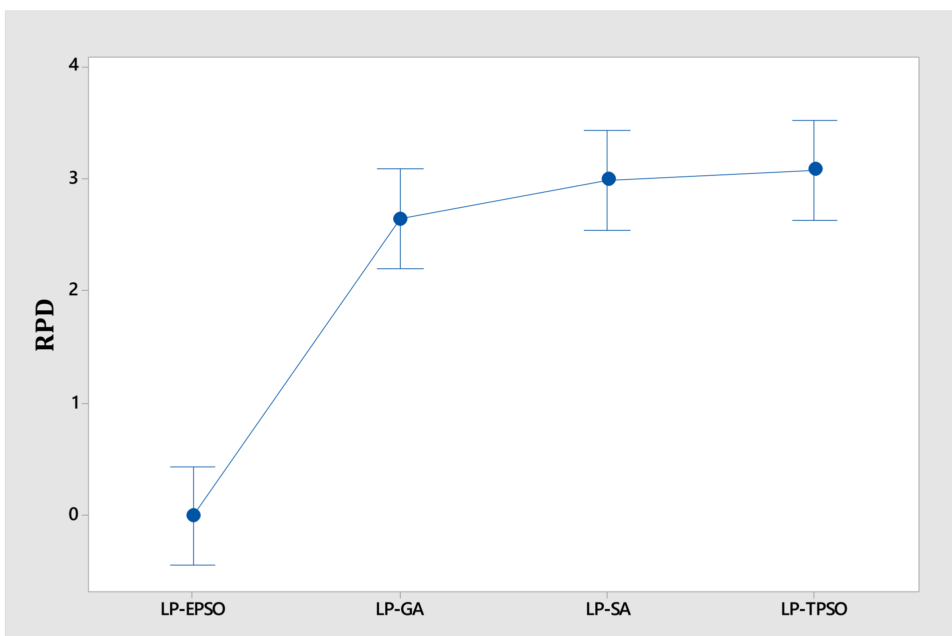


Fig. 15 The performance of the algorithms based on the CPU time metric

Fig. 16 LSD intervals for algorithms based on the RPD metric



under different values for the demand parameter and the results are reported in Fig. 18. According to the obtained results, as the demand size increases, the first OF increases, too. In this regard, the establishment cost is increased due to needing to open more facilities to perform SC's activities. On the other side, an enhancement in the demand size results in enhancing the production, transportation, and distribution activities that lead to increasing these costs (as shown in Fig. 18a). When the demand has increased, the firm has to buy carbon credit, which is the main reason for increasing the other costs in the following chart. On the other side, Fig. 18b indicates that when the demand size increases, the carbon emission also increases.

5.4.2 Interaction between the responsiveness and EIs

This part examines the interrelationships between the responsiveness and environmental criteria. To this end, the

Table 8 Comparing the average value of PRE

Algorithm	PRE	
	$\overline{\text{PRE}}_{\text{Small-sized}}$	$\overline{\text{RPD}}_{\text{Large-sized}}$
LP-SA	2.153	2.99
LP-GA	1.780	2.643
LP-TPSO	2.294	3.08
LP-EPSO	1.435	0

presented model is solved with various values for the service level (SL) and the outputs are demonstrated in Fig. 19. Based on this figure, by enhancing the SL, both the TCs and the EIs have increased. The reason is that by enhancing the SL, the number of established facilities and the production/transportation activities of the SC have increased, which results in increasing the carbon emissions and the TCs. In this regard, when the service level shifts from 0.86 to 0.98, total cost and EIs have increased by 41% and 10%, respectively.

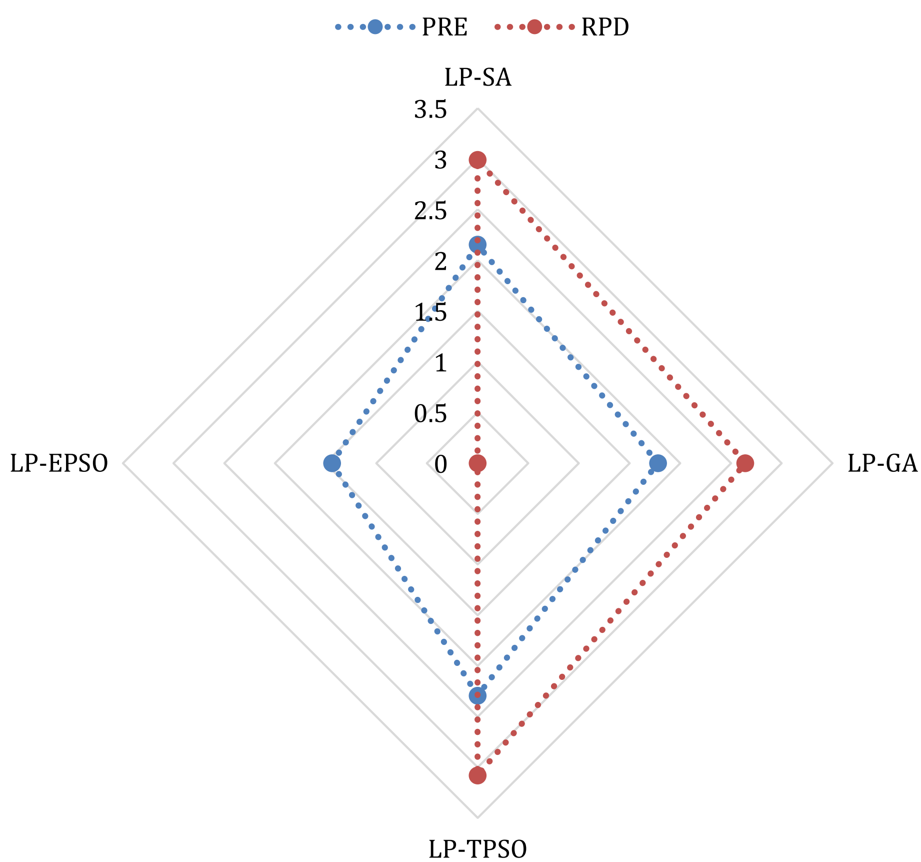
5.4.3 Interaction between the resilience and EIs

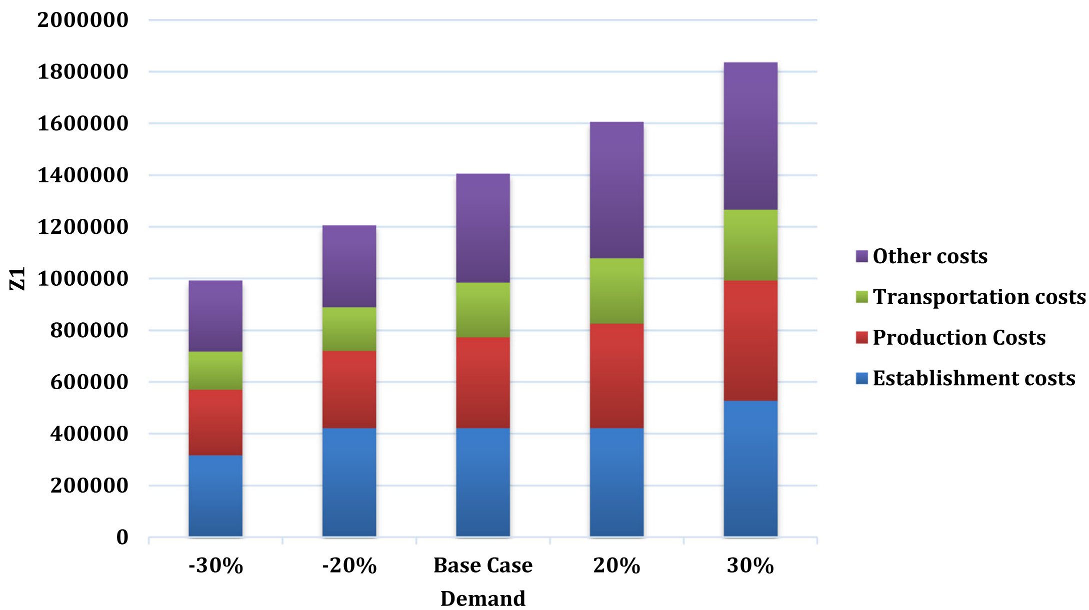
This section is devoted to examining the interaction of resilience and environmental measures. To this end, five different modes have been considered for the disrupted capacity parameters ($\sigma_{is}, \tau_{js}, \rho_{ks}$, and π_{cs}) in which the values of the mentioned parameters are increased by shifting from mode 1 to mode 5. Figure 20 depicts the results of conducting sensitivity analysis. As shown in Fig. 20, by increasing the rate of disruption, the values of the first and second OFs have nonlinearly increased. An increase in the disrupted capacity parameters has led to a 17% enhancement in the TCs and a 7% enhancement in emissions.

5.4.4 Sensitivity analysis on *EmCap*

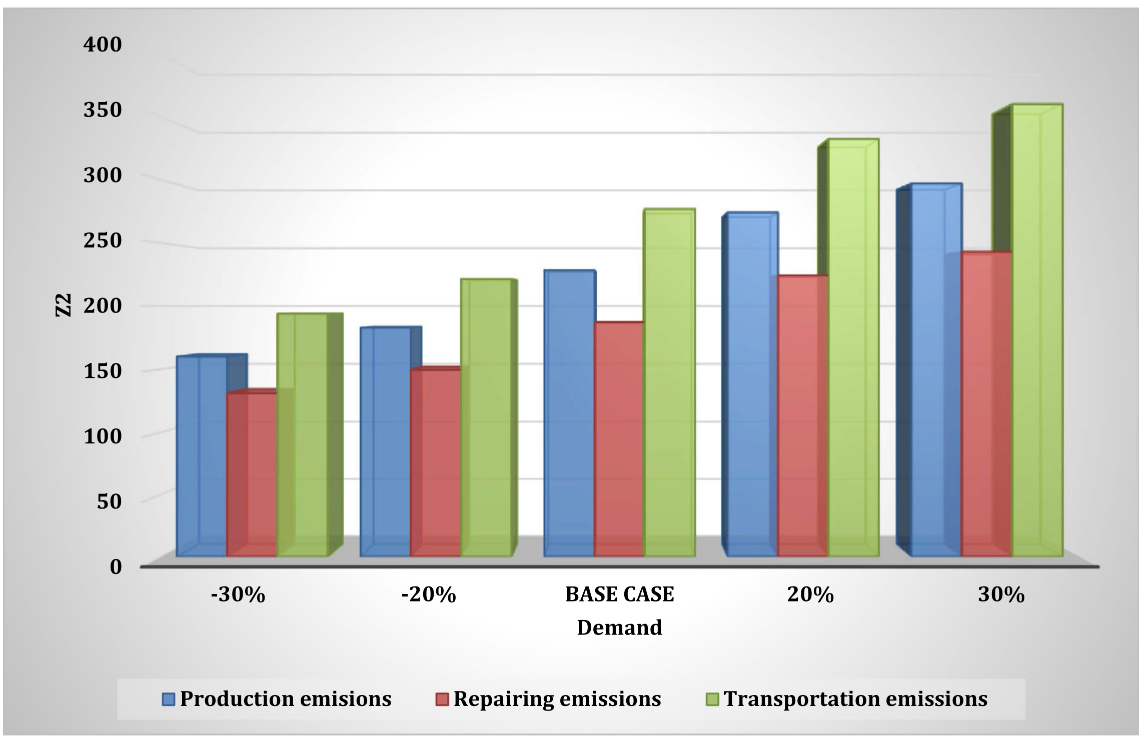
This section attempts to investigate the impact of the carbon cap-and-trade policy on the problem. Based on Fig. 21, an increase in the *EmCap* parameter results in decreasing the TCs and increasing the carbon emissions. In this regard, by increasing *EmCap* from -50% to its base case, carbon emissions are increased by 7%; however, the TC has decreased by 19%. On the other side, by increasing *EmCap* from the base case to the + 30%, the TC has reduced by 9%, but carbon emissions have increased by 3%.

Fig. 17 Comparing the employed algorithm based on the RPD and PRE metrics





(a) The first objective function



(b) The second objective function

Fig. 18 The sensitivity analysis on the demand

5.4.5 Penalty cost coefficient

In this section, the RPS model has been solved with various values for the RPS penalty cost coefficient (φ), and the achieved results are illustrated in Fig. 22. According to this figure, an increase in parameter φ leads to reducing the expected penalty cost; however, it leads to enhancing the expected TCs. According to [64], this behaviour shows the good performance of the RPS model. It is worthy to note that increasing the OF is defined as a robustness price, which is known as the cost of considering uncertainty in the problem.

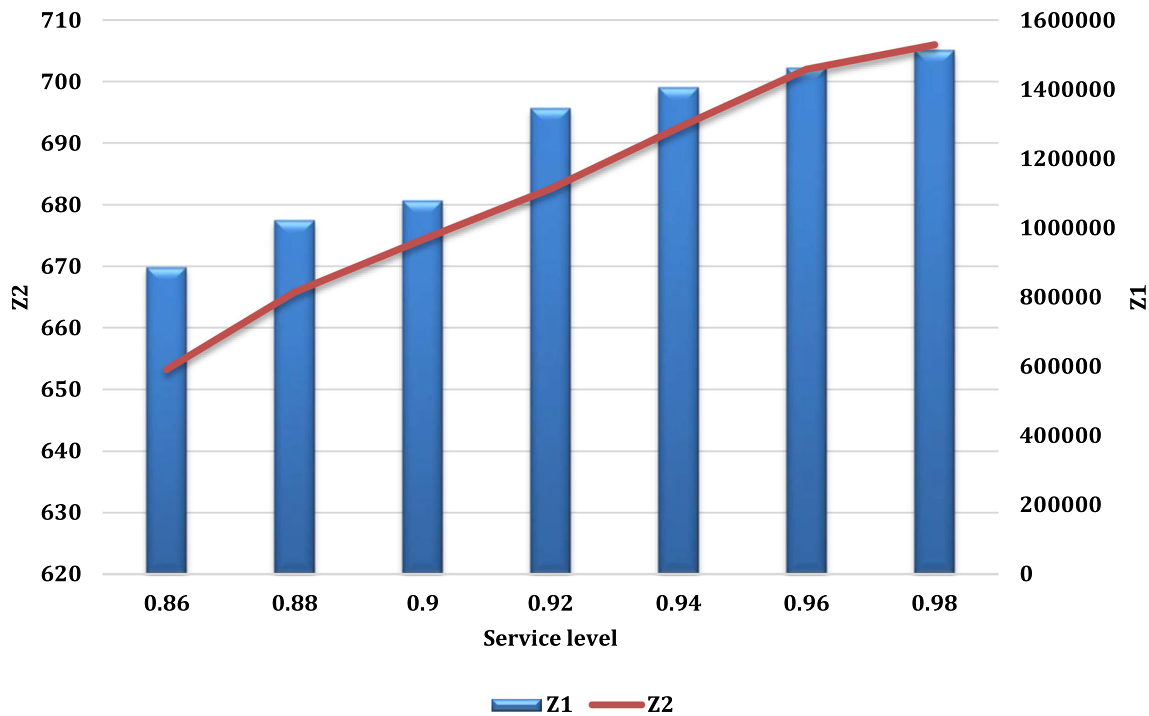


Fig. 19 Interaction between the responsiveness and greenness metrics

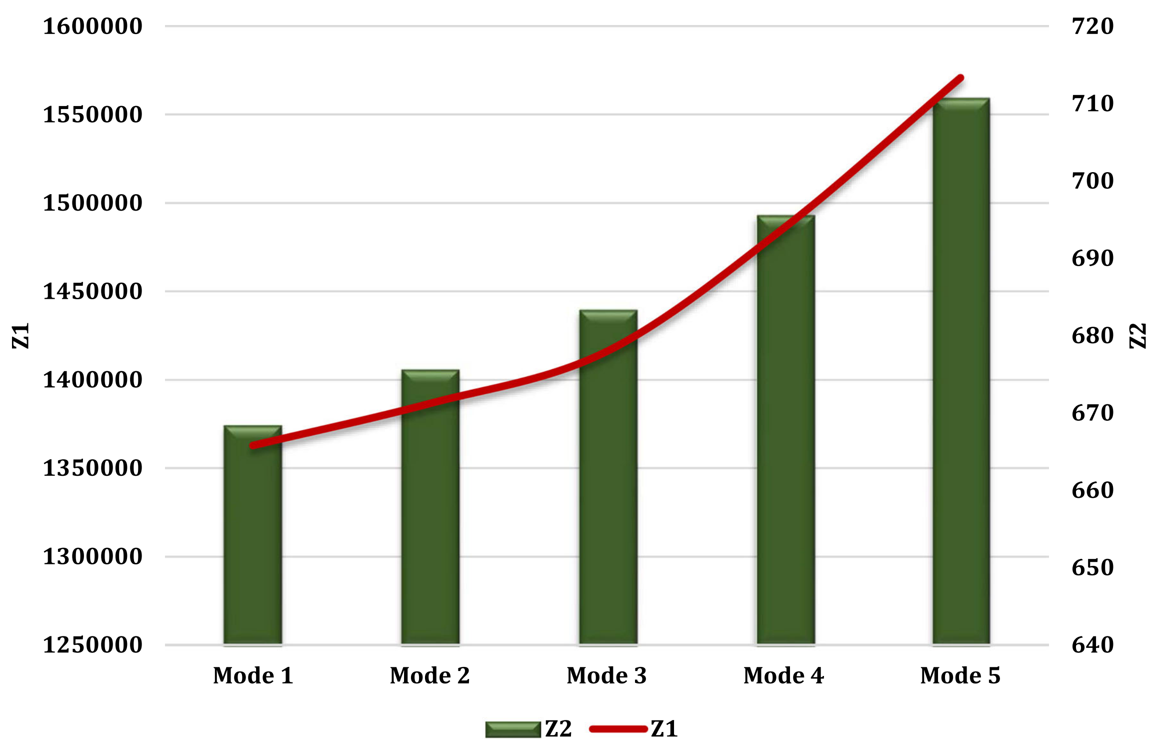


Fig. 20 Interaction between the resilience and greenness metrics

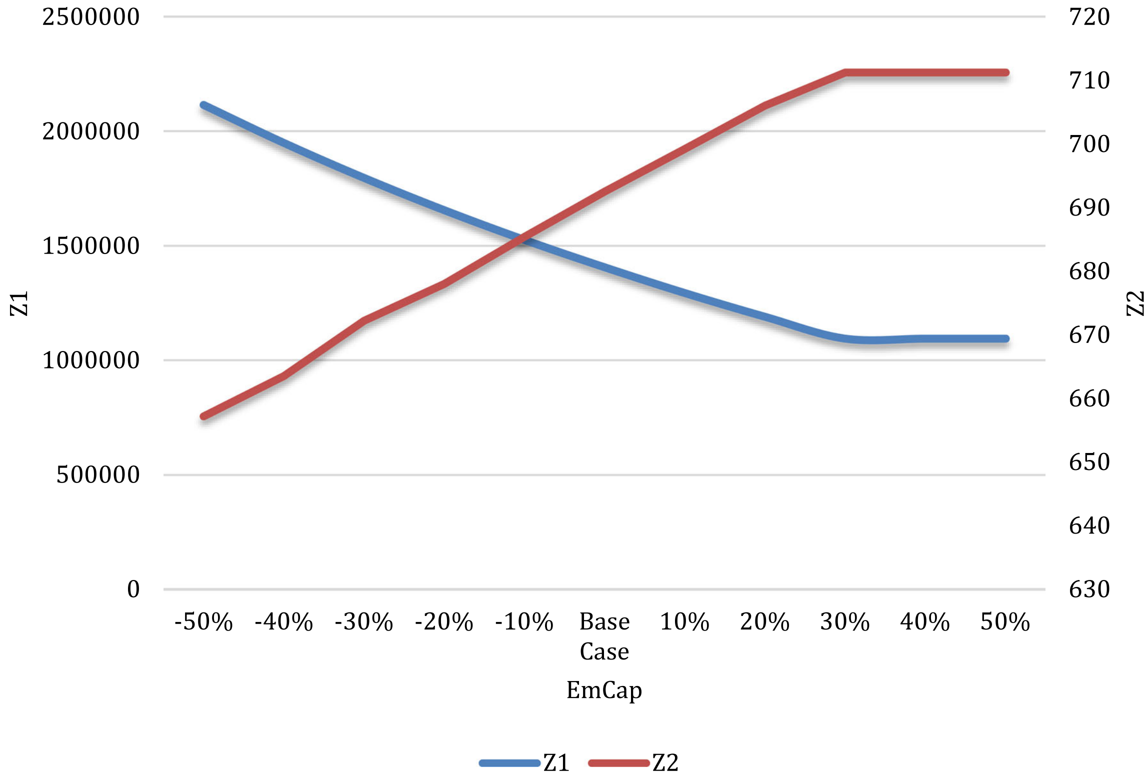


Fig. 21 The outputs of the sensitivity analysis on EmCap

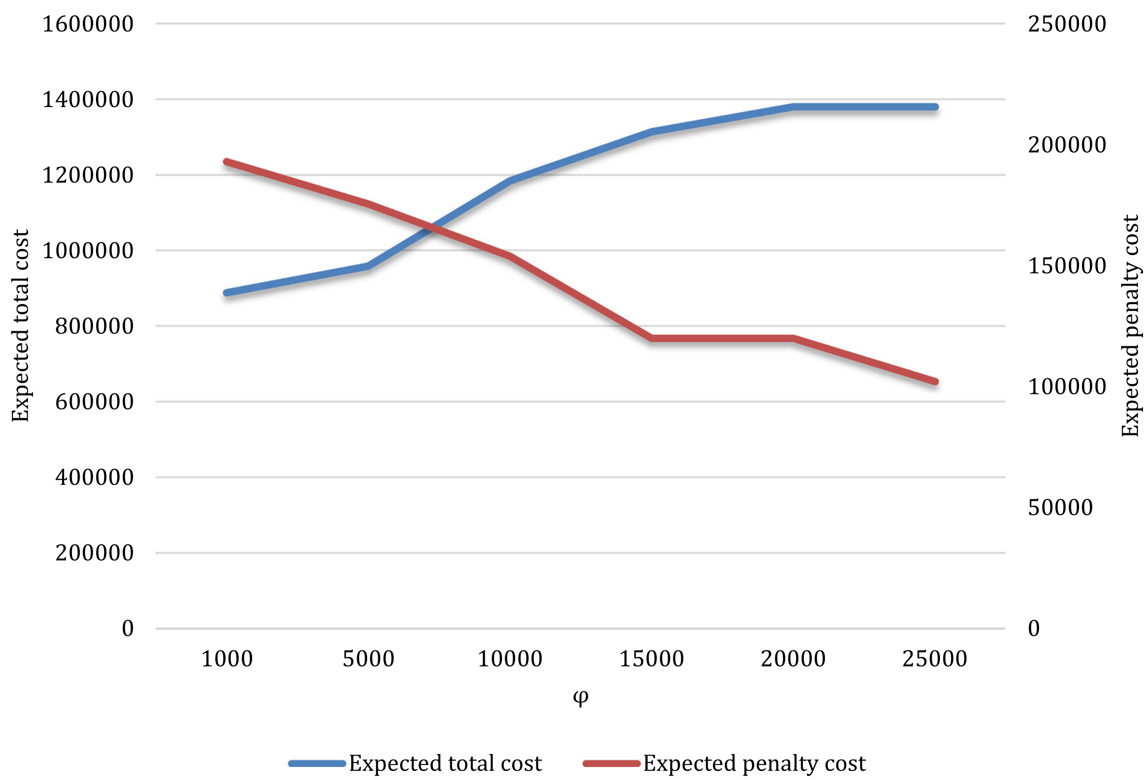


Fig. 22 Sensitivity analysis of parameter φ

Table 9 The results of solving the research problem in different modes

	Deterministic	RPS (satisfaction level = 0.7)	RPS (satisfaction level = 0.8)	RPS (satisfaction level = 0.9)
1	1,210,139.00	1,258,101.00	1,183,090.00	1,177,437.00
2	1,216,114.00	1,339,400.00	1,249,827.00	1,245,075.00
3	1,189,411.00	1,232,221.00	1,223,868.00	1,231,369.00
4	1,209,948.00	1,257,974.00	1,189,260.00	1,172,462.00
5	1,186,096.00	1,249,823.00	1,261,793.00	1,186,568.00
6	1,344,359.00	1,295,143.00	1,212,061.00	1,214,378.00
7	1,370,741.00	1,212,491.00	1,259,885.00	1,232,417.00
Mean	1,246,686.86	1,263,593.29	1,225,683.4	1,208,529.43
SD	71,215.21	38,893.75	30,204.76	27,286.70

5.4.6 Comparing the performance of the RPS model with the deterministic one

In this section, we generate seven test problems and solve them under uncertain and deterministic conditions. Table 9 compares the obtained results. It should be noted that two metrics [the average and the standard deviation (SD)] have been defined to compare the achieved results. In this regard, the model with the less average and SD has better performance. As shown in Table 9, the RPS model has been solved with the various values for the satisfaction level. The outputs demonstrate that the RPS model with $\alpha = 0.8$ and 0.9 has outperformed the deterministic model due to its lower average and SD. However, the performance of the deterministic model is better than RPS with $\alpha = 0.7$.

5.5 Managerial implications

The main managerial implications of this study are presented in this section. In general, this study has studied the design of a green-responsive-resilient SC network under mixed uncertainty. This work provides the following managerial insights.

- The current study can help the decision-makers to better understand the concepts of greenness, responsiveness, and resiliency in SC management. In other words, this research can help managers to gain a good perspective regarding the impact of the environmental, responsiveness, and resilience aspects.
- Since the present work deals with the mixed uncertainty, it can help managers of SC to cope with this major issue (i.e. uncertainty) in their SCs.
- According to Fig. 18a, the TCs have increased by increasing the demand sizes. The model exhibits this behaviour because of the enhancement of the shortage costs due to increasing the demand sizes. To cope with the mentioned issue, strategies like outsourcing and subcontracting can help the system to manage the SC capacity and reduce the TCs.
- According to Fig. 18b, by enhancing the amount of demand, the EIs have increased. To cope with this challenge, utilizing the manufacturing technologies and transportation fleet with lower pollution can be a useful strategy.
- As shown in Fig. 20, the percentage of disrupted capacity has drastically effect on the costs and environmental measures of the SC. Hence, to prevent this adverse effect, leaders of the SC can adopt some strategies such as sub-contracting and establishing more reliable facilities.
- Based on Fig. 21, an increase in the carbon cap parameter has a significant impact on decreasing the TCs. Hence, increasing the bargaining power of the firms to gain more capacity for carbon emissions from corresponding organizations can be dramatically useful.

6 Conclusions

The present work aimed to design an SC network for the oxygen concentrator considering three important factors, namely EIs, resiliency, and responsiveness. In this way, a multi-objective RPS model was suggested, and then an efficient solution method was developed. The obtained results demonstrated the efficiency and validity of the proposed model and developed algorithm. Also, sensitivity analyses have been conducted to show the behaviour of the proposed model due to changing the critical parameters. Since the main scope of the current work is to design an SC under uncertainty, future studies can add other crucial factors in the SC management field such as the social impacts, globalization, and agility in the current problem. On the other side, in terms of contributing to the solution methodology, developing exact methods such as Benders' decomposition to solve the research problem and comparing the results with this study is another direction for future research.

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