Mathematical modeling for the closed-loop supply chain with consideration of sustainability risks: a hybrid optimization approach

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Mathematical modeling for the closed-loop supply chain with consideration of sustainability risks: a hybrid optimization approach

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Abstract
This study presents a novel approach for managing sustainability risks in closed-loop supply chains (CLSCs) through a hybrid optimization model. To achieve this, we utilized published information from previous research to create a questionnaire with four sustainability risks and 18 sub-criteria. In this case, a bi-level mathematical model was proposed that considered the government's concerns regarding sustainability risks at the upper level and at the lower level were the decisions related to the manufacturers' activities in the CLSC network. In addition, a case study was conducted to demonstrate the validity. The findings highlight opportunities for cost reduction and operational efficiency through optimal capacity utilization. Moreover, the model promotes real-world adaptability by considering various scenarios and uncertain demands. Finally, we obtained specific results along with some management implications through a sensitivity analysis. The results of sustainability risk assessment based on a questionnaire and expert opinion showed that economic risks have the most significant impact among other risks.

Keywords Mathematical modeling · Closed-loop supply chain · Optimization approach · Sustainability risk

1 Introduction

In recent decades, supply chain management (SCM) has gained acknowledgment as the oversight of the movement of resources from origin to destination in order to fulfill customer contentment (Valizadeh et al., 2020). Achieving customer needs with minimal cost and superior quality, delivered on time, has remained a fundamental goal of SCM (Tiwari et al., 2016). However, the dynamic market conditions and evolving customer demands pose challenges for companies in attaining these objectives while keeping up with global competition. Consequently, the design and implementation of supply chains (SCs) that incorporate customer needs have emerged as a solution, creating a long-term competitive advantage for companies (Soleimani et al., 2017). It is important to note that historically, SCs primarily focused on raw material production and meeting customer requirements,

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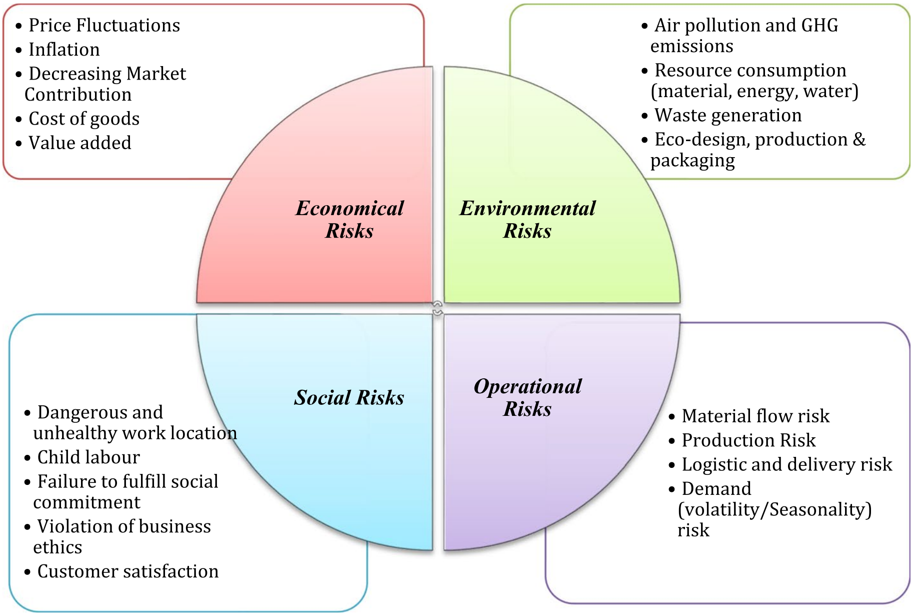


Fig. 1 Dimensions and indicators of sustainability risks

with limited consideration given to waste management and environmental concerns (Boronoos et al., 2021; Liao et al., 2020). Nevertheless, increasing government regulations on waste recycling and growing public awareness of environmental issues have compelled manufacturers to embrace the design of closed-loop supply chains (CLSCs) (Govindan et al., 2015; Zhao et al., 2021).

Stakeholders attach significant value to sustainability aspects as the disregard for these requirements can lead to sustainability risks (SR) (Busse et al., 2016). Sustainability encompasses the impact of organizations' present decisions on the future state of the natural environment, societies, and business viability (Krysiak, 2009). Thus, any risk that jeopardizes the sustainability aspects of organizations qualifies as a sustainability risk and has the potential to harm companies' financial markets and supply chains (Foerstl et al., 2010). Consequently, managing sustainability requirements in the production and service delivery process becomes imperative in mitigating SR and ensuring a sustainable SC (Markley & Davis, 2007). Moreover, recent studies in SCM have emphasized the essential role of government regulations in influencing the interactions between the government and SC members' decisions (Madani & Rasti-Barzoki, 2017). Governments aim to support producers in effectively addressing potential risks. This research aims to propose a sustainable model considering the importance of economic, social, environmental, and operational risks (Fig. 1).

On the other hand, due to market uncertainty, supplier conditions, and customer demand, the CLSC is prone to change. Therefore, uncertainty is a vital part of the design of supply chain networks, especially CLSCs (Tavanayi et al., 2020). In other words, SCs, due to their complex nature, face a high level of uncertainty that can negatively affect the quality of network performance (Imran et al., 2018). Some of these uncertainties include unforeseen demands and product return rates. Designing supply network models without considering uncertainty dramatically reduces the efficiency of these models and significantly increases

SC risks, especially financial risks (Subulan et al., 2012). Overall, this paper examines how a robust bi-level model for a CLSC can be presented by considering sustainability risks. Thus, the model can assist managers in creating a sustainable SC in the polyethylene industry. According to the significance of the mentioned arguments, the research questions are as follows:

a. Given the inevitable risks of SC, how can we minimize the destructive effects of these risks?
b. How can we formulate the interaction between producers and government?
c. How can the importance of SRs be considered in a CLSC model? Is there a method for combining qualitative and quantitative criteria in a CLSC?

In the context of the CLSC problem, it is evident that the integration of social, managerial, and environmental aspects is a critical area that requires further analysis (Abbate et al., 2023). The existing literature on CLSCs has made valuable contributions, but some of the gaps still remain to be addressed. Furthermore, this paper recognizes the pressing need to analyze and incorporate the social, managerial, and environmental dimensions in the design and operation of CLSCs. By doing so, the study seeks to provide a comprehensive understanding of how these dimensions intersect and influence decision-making processes in the context of CLSCs. Integrating these aspects will not only enhance the sustainability performance of CLSCs but also provide valuable insights into minimizing risks and achieving efficient and effective operations.

Therefore, this paper proposes a robust bi-level model that effectively considers sustainability risks in CLSCs. By addressing the identified literature gaps, the model aims to provide a decision support system for managers in establishing CLSCs while prioritizing the importance of sustainability risks. The evaluation model incorporates economic, environmental, social, and operational risks based on government requirements. To ensure the model's practical relevance, it has been applied and validated in a manufacturing company, with all constraints derived from real-world and current conditions. Finally, this study aims to contribute to the existing literature by addressing the identified gaps in the knowledge of CLSCs. By proposing a robust bi-level model that effectively considers sustainability risks and incorporates social, managerial, and environmental dimensions, this research provides valuable insights for managers in establishing sustainable CLSCs. The integration of these dimensions will enable decision-makers to minimize risks, enhance efficiency, and ensure the sustainability of CLSCs.

The subsequent sections of this study are organized as follows: Sect. 2 delves into a comprehensive literature review of CLSC, SR, and Bi-level programming problems. Section 3 introduces the research methodology employed in this study. Section 4 elaborates on the formulation of the model. In Sect. 5, we delve into the calculation of the weight associated with SRs in CLSC. Moving on to Sect. 6, we address the model's solution using real-world data. Finally, in Sect. 7, the study concludes and provides insights into potential avenues for future research.

2 Related works

While a considerable amount of research has already been conducted on forwarding and backward SC design problems, there has been an increasing awareness of CLSC design problems in recent years. This research is closely related to CLSC (with the returned products) and SR, reviewed through the following subsections.

2.1 Research on closed-loop supply chain

Many papers have been published on the CLSC. Pishvaee and Torabi (2010) introduced a two-objective probabilistic mixed integer programming to design a CLSC. In this model, the reverse chain is considered along with the direct chain. The network includes factories, distribution centers, customers, collection centers, recycling and disposal sites, and centers that store broken products and sell raw materials to customers. The model comprises two objective functions, namely cost minimization and latency optimization. The optimization model is Stochastic that is solved by a fuzzy interactive method. Ramezani et al. (2013) presented a robust design for a multi-level and multi-product ring network model under uncertainty conditions, including forwarding and backward flows. Because logistics network design considering the demand uncertainty and various scenarios is time-consuming and costly, robust optimization can help solve these models. Su and Wang (2014) presented a model for designing a closed-loop logistics network that includes suppliers, manufacturers, collection centers, and dismantling centers. The primary goal of this model is to minimize the expenses associated with the logistics network. In addition, a tree-based genetic algorithm of coverage was developed for this model.

Hassanzadeh and Zhang (2014) presented a two-objective model under uncertainty conditions. The closed-loop logistics network in this study encompasses factories, demand markets, collection centers, and landfills. Within the model, there are two primary objective functions: cost minimization and the maximization of the utilization of environmentally friendly raw materials. Reimann et al. (2019) have focused on the link between remanufacturing and the opportunity to reduce the variable cost of remanufacturing through process innovation. Specifically, they look at how the option is used in an SC consisting of a manufacturer and a retailer. Peng Master et al. (2020) Reviewed previous research on the uncertainty inherent in a CLSC. They reviewed 302 articles published in the Web of Science database from 2004 to 2018. The results showed that optimizing the effects of uncertainty in the CLSC could effectively and efficiently achieve sustainable development and cleaner production. Jian et al. (2021) presented a Stackelberg game model of centralized and decentralized decision-making for the green package SC. The decisions of the SC members were analyzed in depth. According to this proposed model, they were designed for a green with fair equity of dividend deal.

2.2 Sustainability risks in the supply chain

Sustainability risks are those risks that may affect economic, environmental, or social aspects (Bashiri et al., 2021). Several studies have been conducted on the identification of various risks, such Tang (2006) and Rao and Goldsby (2009), which are mainly found in manufacturing industries, retail companies, and logistics services. They listed the industries being studied in the field of SC risk management. These industries primarily included aerospace, automotive, food, healthcare products, and apparel and converting industries. There is no holistic view on risks in different studies. Researchers focused on various aspects such as supply risks in Harland et al. (2003) and Zsidisin (2003), outsourcing risks in Lee et al. (2012), and global sourcing in Deane et al. (2009) and Christopher et al. (2011).

Ming et al. (2019) developed a framework for assessing SC sustainability risk by measuring the entire SC's operational, social, and environmental risk to form an aggregated metric. Abdel-Basset and Mohamed (2020) provided the estimation of sustainable supply chain risk management (SSCRM). The results showed the importance of each criterion to assess SSCRM and the classification of the three categories of telecommunication equipment. Chowdhury and Quaddus (2021) developed a combined tool for measuring supply chain sustainability (SCS) using a dynamic capability view and various research methods. Their results show that SCS is a multi-dimensional framework consisting of four dimensions: social, environmental, and economic (financial), and operational (production).

2.3 Bi-level supply chain programming problem

Bi-level programming, an approach to decentralized decision-making in modeling, involves the upper level's goals as those of a leader and the lower level as a follower, as outlined by Roghanian et al. (2007). This type of programming addresses the interaction between the upper and lower levels, as highlighted by Valizadeh et al. (2021a, 2021b, 2021c). Roghanian et al. (2007) presented a probabilistic bi-level linear multi-objective programming problem designed for supply chain planning. Their focus was on a "probabilistic bi-level linear multi-objective programming problem" and its application to enterprise-level supply chain planning, wherein market demand, factory production capacities, and available resources for each product were considered as random variables.

Sadigh et al. (2012) presented a bi-level model for SC consisting of manufacturer and retailer by a Stackelberg game framework under two power scenarios. Amirtaheri et al. (2017) proposed a Stackelberg game framework for the supply chain network and developed a bi-level model to address concerns for manufacturers and distributors. Kaboli Chalmardi and Camacho-Vallejo (2019) presented a bi-level programming model for designing sustainable supply chains, with a specific focus on incorporating incentives for the adoption of cleaner technologies. In the proposed model, a government Environmental Protection Agency led and acted as an upper-level decision-maker. Tantiwattanakul and Dumrongsiri (2019) studied a bi-level decentralized SC, including a single manufacturer and several retailers. Sun and Chen (2020) established a bi-level SC planning model in which the principal firm was the leader, and the suppliers were the followers. The computational results indicated that the proposed model and techniques could provide appropriate tools to tackle the other SC planning problems with hybrid variables in an uncertain decision-making environment. Table 1 provides the details of some studies related to the CLSC.

2.4 Research gaps and contributions

In reviewing the literature and Table 1, it was found that simple models were used to formulate the CLSC questions in previous studies. Moreover, in most of the proposed models, potential sustainability risks are not considered, which may affect the real-world application of the proposed models. Sustainability risks have recently become a significant concern for governments and people worldwide, and their consideration of SCM issues is substantial. On the other hand, reviewing the environmental problems is critical in SCM. Therefore, striving for maximum recycling of returned products must be addressed. Moreover, considering that SC costs are a big part of the product's final cost, a review of the SC process analysis can be a suitable idea.

On the other hand, in SC modeling, there are always parameters whose exact value cannot be estimated in the future. However, we can consider the range or the probability distribution for the importance of these parameters (Maadi et al., 2020). Viewing this uncertain information will lead to a better performance in SC modeling than average estimates

Table 1 Detail of previous researches in the bi-level programming problem and the CLSC

Researcher	Model type		Certainty		Network		Objective		Solution method
	Simple	Bi-level	Uncertain	Certain	Reverse	Forward	Sustainable	Risk	
Yeh and Chuang (2011)	✓			✓		✓			MOGA algorithm
Tseng et al. (2014)	✓		✓			✓			Fuzzy ANP method using
Ghayebloo et al. (2015)	✓			✓		✓			The Pareto front and ε-constraint approach
Giannakis and Papadopoulos (2016)				✓		✓	✓	✓	Statistical methods
Huang et al. (2016)	✓			✓		✓			Genetic algorithm
Lee et al. (2016)						✓	✓	✓	
Soleimani et al. (2017)	✓			✓	✓		✓		The Pareto front and ε-constraint approach
He (2017)	✓			✓	✓			✓	Mathematical definition
Sahebjamnia et al. (2018)	✓			✓	✓				Multi-algorithm
Valinejad and Rahmani (2018)						✓	✓	✓	Statistical methods
Choi and Luo (2019)	✓		✓		✓		✓		-
Darestani and Hemmati (2019)	✓		✓		✓				Three multi-criteria decision-making methods
Xu et al. (2019)				✓	✓		✓	✓	Statistical methods
Zhao and Sun (2019)	✓			✓	✓				The exact solution method
Liao and Li (2021)	✓		✓		✓		✓		The exact solution method
Valizadeh et al. (2020)	✓		✓		✓				Robust optimization
Prakash et al. (2020)	✓		✓		✓			✓	Mixed integer programming formulation
Rezaei et al. (2020)	✓		✓			✓	✓		Game theory
Gholamian et al. (2021)	✓			✓		✓			Fuzzy method
Fazli-Khalaf et al. (2021)	✓		✓			✓	✓		Numerical simulation
Ghasemzadeh et al. (2021)	✓		✓			✓			ε-constraint
Lotfi et al. (2021)		✓	✓		✓		✓	✓	The lagrange relaxation and fix-and-optimize algorithm
Chowdhury and Quaddus (2021)				✓		✓	✓	✓	Statistical methods
Zhu et al. (2022)	✓			✓		✓	✓		Numerical simulation
Rajak et al. (2022)	✓		✓			✓	✓		Numerical simulation

Table 1 (continued)

Researcher	Model type		Certainty		Network		Objective		Solution method
	Simple	Bi-level	Uncertain	Certain	Reverse	Forward	Sustainable	Risk	
The present research (2024)		✓	✓		✓		✓	✓	Robust optimization

(Khorshidi & Aickelin, 2020). One such method of dealing with uncertainty, which has found many applications in real-world problems, is the robust optimization method (Valizadeh et al., 2021a, 2021b, 2021c). Based on this, we presented a model that has the following innovations:

i. As a first innovation, we introduced a novel bi-level model for closed-loop supply chain (CLSC) management, where the government assumes the leadership role at the upper level. This model is designed to address governmental concerns regarding sustainability risks. The government, by implementing specific decisions and policies, aims to effectively manage sustainability risks, encompassing economic, environmental, social, and operational risks. Our primary objective is to optimize the upper level of the model by prioritizing sustainability risks and assigning appropriate weights to each of these risks.
ii. At the lower level, we took into account the activities model involving product manufacturers, who adhere to the decisions set forth by the government. Both production and distribution networks are directly affected by potential sustainability risks. The government would manage a large part of the existing risks by making decisions and implementing specific policies. Government policies in this area help manufacturers minimize the costs of the entire SC. The total cost includes the cost of supplying raw materials, the cost of producing new products, the cost of recycling returned products, and the cost of transporting and distributing products, which must be minimized.
iii. Considering the inherent uncertainties that prevail in the real-world scenario, uncertainty plays a crucial role in SC matters. To address the existing uncertainties, we have incorporated stochastic parameters into our analysis. In this study, the uncertainty stems from the number of returned products, which is contingent on the production quantity. To obtain optimal solutions, the Benders method is applied to tackle the presented bi-level model. Lastly, the effectiveness of the proposed model is assessed using real-world data from a manufacturing company in the form of a case study.

3 Methodology

This section is divided into three main parts. We identified the main risks using the field study and reviewed various sources in the first part. Following the identification of the primary criteria and sub-criteria, the sub-criteria related to SR are further analyzed in the second section of this study through a combination of questionnaires and expert interviews. The most suitable sub-criteria are selected to rank the sustainable risks. Subsequently, the CLSC criteria and sub-criteria weighting is carried out through the analytic network process (ANP) approach and pairwise comparison matrices (through expert interviews). The outcomes of this phase serve as inputs for the upper level of the mathematical model. In the third part of this research, this classification is employed to address the requirements of both the government and the manufacturers. Consequently, a bi-level mathematical model is employed, and Fig. 2 provides an overview of the processes in these phases.

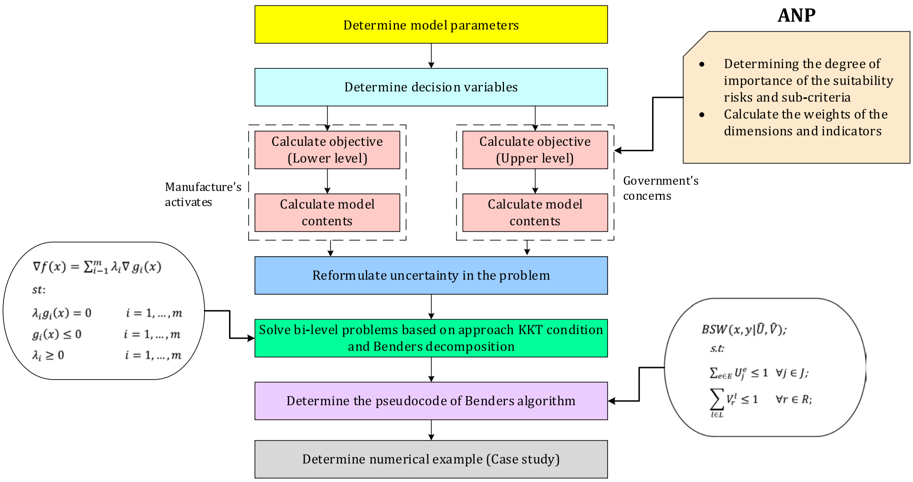


Fig. 2 Proposed methodology for sustainable risks in CLSC

4 Formulation of the model

As stated in the previous sections, the question of this study considers two concerns related to sustainable risks and total costs of CLSC in the form of a bi-level model. The ANP method with a fuzzy approach was used in this research to identify and weigh sustainable risks. Therefore, by prioritizing each of the four realized categories, including economic, environmental, social, and operational risks, the impact of each of these criteria on the upper level of the model is determined. This is while the upper level of the model is related to the lower level due to standard variables and affects it directly. Therefore, the lower level of the model, which is to minimize the costs of the entire CLSC, is considered a concern for manufacturers. These costs include fixed costs of setting up factories and warehouses, potential production costs, product transportation, and distribution costs, product recycling costs, and complications related to the disposal of defective products. In the proposed model, according to customer demand, products are produced by factories and then transported to warehouses and from there to customers. However, there are always potential risks to sustainability at each production, transportation, and distribution stage. This study has tried to minimize government and manufacturers' concerns at upper and lower levels. Based on this, we have considered a bi-level model, the general outline of which is shown in Fig. 3.

With conflicting concerns, the government is trying to operate SC networks within sustainability standards, considering sustainability risks. On the other hand, manufacturers are trying to reduce the cost of the whole network and optimize production and distribution activities so that all customer demand is met. In other words, decision-making appears at both the two-level (leader and followers) in an optimization problem. The leader decides, and the followers react based on that, so the objective is optimized based on the follower's behavior (Valizadeh et al., 2021a, 2021b, 2021c). In this research, we have taken into account the following four assumptions to better conceptualize certain ideas:

Assumption 1 The location of the potential facility has been determined. In other words, we did not look for optimal points for the construction of factories and warehouses (if

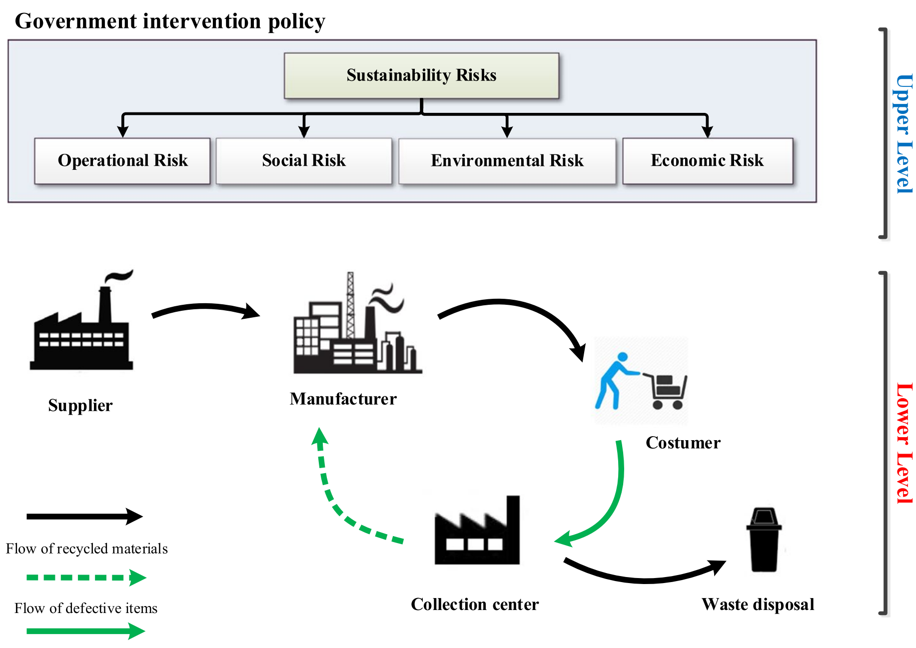


Fig. 3 Proposed leader–follower model

necessary). In the case of establishing a new factory or warehouse, its construction location has been determined in advance.

Assumption 2 The rate of return on products is stochastic. In other words, we do not consider a fixed product failure rate, and by assuming a stochastic parameter, we assume that this value is random.

Assumption 3 The production and storage capacity of the products is apparent. For this purpose, to increase the capacity level, it is necessary to create a new factory or warehouse.

Assumption 4 In the basic model, all customer demands should be met. In other words, lack of demand is not allowed in this research, and all customer demand should be covered.

In general, in SC under study, potential suppliers, factories, and warehouses produce and distribute the required products. There are also options for creating a new factory or warehouse (the collection centers) that collect the returned products from customers, carry out the necessary processing operations to recycle and reproduce products, and their construction requires an initial establishment cost. The parameters and variables used for modeling are given below:

The indexes	
i	Index of customers
j	Index of production centers (factories)
v	Index of raw material suppliers

k	Index of warehouse
g	Index of the collection center
o	Index of disposal locations
h	Index of raw materials
f	Index of all types of products
r	Index of the type of sustainability risks
p	Index of defective products
e	Index of different capacity levels for production centers (factories)
l	Index of different capacity levels for warehouses
The parameters	
cf_j^e	Fixed cost of setting up a factory j with capacity level e
cl_k^l	Fixed cost of setting up a warehouse k with a capacity level of l
cs_{hfv}	Cost of supply of raw materials h to produce a unit of product f by the supplier v
cp_{fij}	Cost of producing one unit of product f for customer i by factory j
ch_{hvj}	Cost of transporting one unit of raw material h from supplier v to factory j
cn_{fjk}	Cost of transporting one unit of product f from factory j to warehouse k
cm_{fki}	Cost of distributing a product unit f from warehouse k to customer i
ct_{pgj}	The cost imposed for collecting product p by collection center g and recycling (reproduction) of defective by factory j
co_{po}	Complications related to the disposal of each unit of defective product p at the disposal site o
rs_{hfv}^r	The relative risk of type r to supply the raw material h required to produce each unit of product f by the supplier v
rp_{fj}^r	The relative risk of type r for the production of each unit of product f by the factory j
rh_{hvj}^r	The relative risk of type r for transporting each unit of raw material h from supplier v to factory j
rt_{fijk}^r	The relative risk type r for transporting each unit of product f between factory j and warehouse k and customer i
rc_{pi}^r	The relative risk of type r to collect and recycle each defective product unit p from the customer i
rd_{po}^r	The relative risk of type r for disposal of each unit of defective product p at disposal site o
α_{fi}	Customer's demand i of product f
v_f	Product volume f
π_f	Average product failure rate f
β_j^e	The capacity level e for production in the factory j
e_k^l	The capacity level l for warehouse k
w^r	Weight calculated for risk type r
M	A large number
The decision variables	
X_{hfv}	The number of raw materials h required to produce product f supplied by the supplier v
Y_{fij}	The number of products f produced for customer i by factory j
Q_{fjk}	The number of products f transferred from factory j to warehouse k
W_{pji}	The number of defective products p collected from customer's location i and reproduced by factory j
T_{pjo}	The number of defective products p collected from customer's location i and disposed of by disposal location o

U_j^e	The variable zero–one is equal to 1 if a factory with capacity level e is set up in location j
V_k^l	The zero–one variable is equal to 1 if a warehouse with a capacity level l is set up at location k

The following equations are used to formulate the desired problem:

$\mathcal{A} = \sum_{r\in R}\sum_{f\in F}\sum_{h\in H}\sum_{i\in I}\sum_{v\in V} w^r rs_{hfv}^r \alpha_{fi} X_{hfv}$	Sustainable risks of raw material supply
$\mathcal{B} = \sum_{r\in R}\sum_{f\in F}\sum_{i\in I}\sum_{j\in J} w^r rp_{fj}^r \alpha_{fi} Y_{fij}$	Sustainable risks of productions
$\mathcal{C} = \sum_{r\in R}\sum_{f\in F}\sum_{h\in H}\sum_{j\in J}\sum_{v\in V} w^r rh_{hvj}^r X_{hfv}$	Sustainable risks of raw material transportation
$\mathcal{D} = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{k\in K}\sum_{r\in R}\sum_{l\in L} w^r rt_{fijk}^r e_k^l Q_{fjk}$	Sustainable risks of transportation and distribution of final products
$\mathcal{E} = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{p\in F}\sum_{r\in R} w^r rc_{pi}^r W_{fji}$	Sustainable risks of products recycling (reproduction)
$\mathcal{F} = \sum_{o\in O}\sum_{j\in J}\sum_{p\in F}\sum_{r\in R} w^r rd_{po}^r T_{pjo}$	Sustainable risks of disposing of defective products
$\mathcal{H} = \sum_{j\in J}\sum_{e\in E} cf_j^e U_j^e + \sum_{k\in K}\sum_{l\in L} cl_k^l V_k^l$	Fixed costs of setting up potential factories and warehouses
$\mathcal{K} = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{h\in H}\sum_{v\in V} cs_{hfv} \alpha_{fi} X_{hfv}$	Costs related to the supply of raw materials
$\mathcal{L} = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F} cp_{fij} \alpha_{fi} Y_{fij}$	Costs related to the production of products
$\mathcal{M} = \sum_{i\in N}\sum_{j\in J}\sum_{f\prime\in F}\sum_{k\in K} (cn_{fjk} + cm_{fki}) Q_{fjk}$	Costs related to transportation and distribution of products
$\mathcal{N} = \sum_{i\epsilon N}\sum_{p\epsilon M} ct_{pj} W_{pji}$	Costs related to product recycling (reproduction)
$\mathcal{O} = \sum_{o\in O}\sum_{j\in J}\sum_{p\in F} co_{po} T_{pjo}$	Complications related to disposing of defective products

Thus, the linear programming problem of CLSC under sustainable risks is in the form of relations (1) to (12).

$$\text{Min } Z_1 = \mathcal{A} + \mathcal{B} + \mathcal{C} + \mathcal{D} + \mathcal{E} + \mathcal{F} \tag{1}$$

s.t.

$$\sum_{v\in V} X_{hfv} = 1 \quad \forall h \in H, f \in F \tag{2}$$

$$\sum_{i\epsilon N}\sum_{e\in E} Y_{fij}\beta_j^e \le \sum_{h\in H}\sum_{v\in V} X_{hfv}\alpha_{fi} \quad \forall j \in J, f \in F \tag{3}$$

$$\sum_{j\in J} Y_{fij} = 1 \quad \forall i \in N, f \in F \tag{4}$$

$$\sum_{i\in N} Y_{fij} - \sum_{k\epsilon K} Q_{fjk} = 0 \quad \forall j \in J, f \in F \tag{5}$$

$$\pi_f Y_{fij} \ge M.W_{pji} \quad \forall i \in N, j \in J, f \in F, p \in F \tag{6}$$

$$\sum_{k\in K}\sum_{f\in F}\sum_{l\in L} e_k^l Q_{fjk} \le \sum_{i\in N}\sum_{f\in F}\sum_{e\in E} \beta_j^e Y_{fij} \quad \forall j \in J \tag{7}$$

$$\sum_{e \in E} U_j^e \le 1 \quad \forall j \in J \tag{8}$$

$$\sum_{i \epsilon N} W_{pji} = 1 \quad \forall p \in F, j \in J \tag{9}$$

$$\sum_{k \epsilon K} Q_{fjk} \le \sum_{i \epsilon N} Y_{fij} \quad \forall j \in J, f \in F \tag{10}$$

$$\begin{aligned} &X_{hfv} \ge 0,\ Y_{fij} \ge 0,\ Q_{fjk} \ge 0,\ W_{pji} \ge 0,\ \forall i \in N, \\ &j \in J,\ h \in H,\ v \in V, f \in F,\ p \in F \quad \text{and} \quad k \in K \end{aligned} \tag{11}$$

$$U_j^e \in (0, 1)\ \forall j \in J \text{ and } e \in E \tag{12}$$

Within this model, Eq. (1) signifies the upper-level objective function, encompassing the sustainability risks related to government concerns, which must be minimized. Constraint (2) indicates that at least one unit of raw materials is supplied for production. Constraint (3) indicates that the number of products produced shall not exceed the number of raw materials supplied to produce those products. Constraint (4) ensures that at least one product is manufactured in the factory. Constraint (5) indicates that the number of products produced equals the number shipped. In other words, no product is stored in the factory, and all products are transferred to warehouses. Constraint (6) ensures that defective products exceed the total produced number. Constraint (7) relates to the capacity limit of factories and warehouses. Constraint (8) ensures that at least one factory is set up to produce the products. Constraint (9) ensures that there is at least one defective product. Constraint (10) indicates that the number of products sent to the warehouse does not exceed the total number of products produced. Constraint (11) imposes a limitation on the non-negativity of continuous variables, while Constraint (12) represents the binary variable.

The lower-level model is also designed as relations (13) to (22):

$$\text{Min } Z_2 = \mathcal{H} + \mathcal{K} + +\mathcal{L} + \mathcal{M} + \mathcal{N} + \mathcal{O} \tag{13}$$

s.t.

$$\sum_{o \in O} T_{pjo} = 1 \quad \forall p \in F, j \in J \tag{14}$$

$$\sum_{k \in K} Q_{fjk} = 1 \quad \forall i \in N, f \in F \tag{15}$$

$$\sum_{i \epsilon N} W_{pji} + \sum_{o \in O} T_{pjo} \le \sum_{k \in K} Q_{fjk} \quad \forall p \in F, j \in J, f \in F \tag{16}$$

$$\sum_{i \in N} \sum_{f \in F} \alpha_{fi} v_f Y_{fij} \le \sum_{e \in E} \beta_j^e U_j^e \quad \forall j \in J \tag{17}$$

$$\sum_{j\in J}\sum_{e\in E}\sum_{f\in F}\beta_j^e Q_{fjk} \le e_k^l V_k^l \quad \forall k \in K \tag{18}$$

$$\sum_{l\in L} V_k^l \le 1 \quad \forall k \in K \tag{19}$$

$$T_{pjo} \ge 0, Q_{fjk} \ge 0 \; \forall p \in F, k \in K, j \in J, o \in O \quad \text{and} \quad f \in F \tag{20}$$

$$V_k^l \in (0,1) \; \forall k \in K \quad \text{and} \quad l \in L \tag{21}$$

In this model, Eq. (13) depicts the lower-level objective function, encompassing the total costs associated with the closed-loop supply chain (CLSC). Constraint (14) indicates that at least one defective product in the network is not recyclable and needs to be eliminated. Constraint (15) ensures that at least one product is sent from the factory to the warehouse. Constraint (16) indicates that the total of products recycled and disposed of must not be greater than those produced. Constraint (17) ensures that all customer demands covered by a factory do not exceed its capacity. Constraint (18) indicates the capacity limit of warehouses. Constraint (19) ensures that at least one warehouse is set up to store and distribute products. Finally, Constraint (20) sets the constraint on nonnegative continuous variables. Finally, Constraint (21) is the zero–one constraint of the variable V_k^l.

4.1 The robust optimization approaches

Mulvey et al. (1995) introduced a robust optimization model that aims to provide solutions that are nearly optimal and nearly feasible under a wide range of likely scenarios. The extent of "almost" depends on the perspective of the modeler. In both robust feasibility solutions and robust optimization modeling, there are penalties associated with the objective functions as determined by the decision-maker. The general form of a robust optimization model is outlined as follows:

$$\text{Min} Z = \sigma\left(x, y_1, y_2, \dots, y_n\right) + \omega\rho\left(\delta_1, \delta_2, \dots, \delta_s\right), \tag{22}$$

s.t:

$$Ax = b; \tag{23}$$

$$B_s x + C_s y_s + \delta_s = e_s, \quad \forall s \in \Omega; \tag{24}$$

$$y_s x \ge 0, \ge 0, \quad \forall s \in \Omega; \tag{25}$$

Within this model, the variables are defined as follows: x is a design variable, y is a control variable, and B_s, C_s, and e_s are parameters influenced by the scenario. The error vector δ_s represents an infeasibility criterion in control constraints under varying scenarios. Equation (23) represents a structural constraint, and Eq. (24) represents a control constraint, as detailed by Valizadeh et al. (2021a, 2021b, 2021c).

Equation (22) has two components. The first part, as indicated by Akbari et al. (2021), pertains to the robustness of the solution and assesses how close the solution is to optimality across all scenarios. The second part, as described by Valizadeh et al. (2020), serves as a criterion for the model's robustness, verifying the feasibility of the model in various likely scenarios. In essence, it identifies control constraints that may need adjustment in scenarios where they breach the model's feasibility constraints. In Eq. (22), the variable ω assesses the relationship between the model's optimality and feasibility. For instance, when ω= 0, it suggests that the solution may lie outside the feasible space (i.e., it is infeasible). Conversely, if the value of the model is sufficiently high, it not only ensures the model's feasibility across different scenarios but also results in increased costs, as highlighted by Valizadeh et al. (2023, 2022). Mulvey et al. (1995) proposed an appropriate definition for $\sigma(x, y_1, y_2, \ldots, y_n)$ as follows:

$$\sigma(x, y_1, y_2, \ldots, y_n) = \sum_{s\in S} P_s\zeta_s + \lambda \sum_{s\in S} P_s\left(\zeta_s - \sum_{s'\in S} P_{s'}\zeta_{s'}\right) \tag{26}$$

The variability weight (λ) signifies the degree of sensitivity of the objective function to variations in the input data across various scenarios. Notably, as per Valizadeh et al. (2023), the variability (or variance) tends to decrease as λ increases. Additionally, we defined $\rho(\delta_1, \delta_2, \ldots, \delta_s)$ as follows:

$$\rho(\delta_1, \delta_2, \ldots, \delta_s) = \sum_{s\in S} P_s\delta_s \tag{27}$$

Hence, the objective function of the model can be reformulated as follows:

$$\text{Min } Z = \sum_{s\in S} P_s\zeta_s + \lambda \sum_{s\in S} P_s\left(\zeta_s - \sum_{s'\in S} P_{s'}\zeta_{s'}\right) + \omega \sum_{s\in S} P_s\delta_s \tag{28}$$

The model is recalibrated under conditions of uncertainty by employing robust optimization and applying Mulvey's approach, and defined in the previous section changes as follows:

In addition to the sets defined in the previous section,

$s = \{1, \ldots ., S\}$, A set of all possible scenarios

The customer demand parameter changes as follows; other parameters are used in the previous setting.

α_{fi}^{s}	The demand of product f by customer i per unit of time for scenarios s
ρ^{s}	Probability of occurrence of scenario s

As with the parameters, some of the variables defined in the previous section are modified, and other variables are used as before.

X_{hfv}^{s}	The number of raw materials h required to produce product f supplied by supplier v in scenario s
Y_{fij}^{s}	The number of products f distributed to customer i produced by factory j in scenario s
Q_{fjk}^{s}	The number of products f transferred from factory j with capacity level e to warehouse k in scenario s
W_{pji}^{s}	The number of defective products p collected from customer i and reproduced by factory j in scenario s
T_{pjo}^{s}	The number of defective products p collected from customer i and disposed of by the disposal center o in scenario s

To use the parameters and variables, the problem equations are expressed as follows:

$\mathcal{A}^s = \sum_{r\in R}\sum_{f\in F}\sum_{h\in H}\sum_{i\in I}\sum_{v\in V} w^r rs^r_{hfv}\alpha_{fi}X^s_{hfv}$	Sustainable risks of raw material supply under scenario s
$\mathcal{B}^s = \sum_{r\in R}\sum_{f\in F}\sum_{i\in I}\sum_{j\in J} w^r rp^r_{fj}\alpha_{fi}Y^s_{fij}$	Sustainable risks of productions under scenario s
$\mathcal{C}^s = \sum_{r\in R}\sum_{f\in F}\sum_{h\in H}\sum_{j\in J}\sum_{v\in V} w^r rh^r_{hvj}X^s_{hfv}$	Sustainable risks of raw material transportation under scenario s
$\mathcal{D}^s = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{k\in K}\sum_{r\in R}\sum_{l\in L} w^r rt^r_{fijk}e^l_k Q^s_{fjk}$	Sustainable risks of transportation and distribution of final products under scenario s
$\mathcal{E}^s = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{p\in F}\sum_{r\in R} w^r rc^r_{pi}W^s_{pji}$	Sustainable risks of products recycling (reproduction) under scenario s
$\mathcal{F}^s = \sum_{o\in O}\sum_{j\in J}\sum_{p\in F}\sum_{r\in R} w^r rd^r_{po}T^s_{pjo}$	Sustainable risks of disposing of defective products under scenario s
$\mathcal{H} = \sum_{j\in J}\sum_{e\in E} cf^e_j U^e_j + \sum_{k\in K}\sum_{l\in L} cl^l_k V^l_k$	Fixed costs of setting up potential factories and warehouses
$\mathcal{K}^s = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F}\sum_{h\in H}\sum_{v\in V} cs_{hfv}\alpha_{fi}X^s_{hfv}$	Costs related to the supply of raw materials under scenario s
$\mathcal{L}^s = \sum_{i\in N}\sum_{j\in J}\sum_{f\in F} cp_{fij}\alpha_{fi}Y^s_{fij}$	Costs related to the production of products under scenario s
$\mathcal{M}^s = \sum_{i\in N}\sum_{j\in J}\sum_{f''\in F}\sum_{k\in K}(cn_{fjk} + cm_{fki})Q^s_{fjk}$	Costs related to transportation and distribution of products under scenario s
$\mathcal{N}^s = \sum_{i\epsilon N}\sum_{p\epsilon M} ct_{pj}W^s_{pji}$	Costs related to product recycling (reproduction) under scenario s
$\mathcal{O}^s = \sum_{o\in O}\sum_{j\in J}\sum_{p\in F} co_{po}T^s_{pjo}$	Complications related to disposing of defective products under scenario s

In addition to the sets defined in the previous section,

λ Coefficient of the significance of variability;

ω Model feasibility coefficient;

As with the parameters, some of the variables defined in the previous section are modified, and others are used as before.

θ^s Variation variables of objective functions;

δ^s_i Control limit violation variable;

The robust model is represented by Equations A1 through An in Appendix. In this research, probabilities are contingent upon different scenarios, with each scenario providing a description of a potential future situation.

4.2 The Karush–Kuhn–Tucker (KKT) conditions and the Benders decomposition method

To tackle bi-level problems, particularly when the problem is both convex and finite, a transformation into a one-level problem can be achieved by applying Karush–Kuhn–Tucker (KKT) conditions, as explained by Valizadeh et al. (2021a, 2021b, 2021c). This approach is one of the most prevalent methods for addressing such problems, where the lower-level problem is integrated into the upper-level problem via KKT conditions, effectively converting the problem into a single-level one. The KKT conditions, which serve as necessary conditions for optimization, are as follows:

$$\nabla p(x) = \sum_{i-1}^{m} \lambda_i \nabla g_i(x) \tag{29}$$

s.t.

$$\lambda_i g_i(x) = 0 \quad i = 1, \dots, m \tag{30}$$

$$g_i(x) \le 0 \quad i = 1, \dots, m \tag{31}$$

$$\lambda_i \ge 0 \quad i = 1, \dots, m \tag{32}$$

The Benders decomposition method pertains to the analysis of an integer programming model, combining a master problem and a subproblem that are solved iteratively using each other's outcomes, as outlined by Valizadeh (2020). The subproblem involves continuous variables and their associated constraints, while the master problem encompasses integer variables and a linking constant connecting the two problems, as introduced by Benders (1962). The Benders decomposition method applicable to our specific problem is presented as follows:

$$\text{Min}(Z) = \mathcal{H} + \text{BSF}(x, y|\hat{U}, \hat{V}) \tag{33}$$

s.t:

$$\sum_{e \in E} U_j^e \le 1 \quad \forall j \in J \tag{34}$$

$$\sum_{l \in L} V_k^l \le 1 \quad \forall k \in K \tag{35}$$

where $\text{BSF}(x, y|\hat{U}, \hat{V})$ is a subproblem of the Benders, the details of which are given in Appendix 1.

4.2.1 Subproblem of the Benders

The static constraints are derived directly from the Lagrange function corresponding to the lower-level problem's objective function. To construct the Lagrange function, you first express the constraints of the second-level model within the robust optimization framework. These constraints, which take the form of (≤ 0) or (≥ 0), are represented by Eqs. (A5, A7, A11, A13 and A14) in Appendix 1. Then, the Lagrange coefficients or dual variables on the left side are multiplied by the rewritten bounds. The subproblem, denoted as $\text{BSF}(x, y|\hat{U}, \hat{V})$, is a minimization problem aimed at finding the optimal values for the continuous variables (x, y) while holding the fixed variables $(\hat{U}, \hat{V})$ constant. This problem can be expressed as follows:

$$\min \mathcal{A}^s + \mathcal{B}^s + \mathcal{C}^s + \mathcal{D}^s + \mathcal{E}^s + \mathcal{F}^s + \mathcal{K}^s + \mathcal{L}^s + \mathcal{M}^s + \mathcal{N}^s + \mathcal{O}^s \tag{36}$$

s.t.

$$\sum_{v \in V} X_{hfv}^s \le 1 \quad \forall h \in H, f \in F, s \in S \tag{37}$$

$$\sum_{v \in V} X_{hfv}^s \ge 1 \quad \forall h \in H, f \in F, s \in S \tag{38}$$

$$\sum_{j \in J} Y_{fij}^{s} \leq 1 \quad \forall i \in N, f \in F, s \in S \tag{39}$$

$$\sum_{j \in J} Y_{fij}^{s} \geq 1 \quad \forall i \in N, f \in F, s \in S \tag{40}$$

$$\sum_{k \in K} Q_{fjk}^{s} \leq 1 \quad \forall i \in N, f \in F, s \in S \tag{41}$$

$$\sum_{k \in K} Q_{fjk}^{s} \geq 1 \quad \forall i \in N, f \in F, s \in S \tag{42}$$

$$\sum_{i \epsilon N} W_{pji}^{s} \leq 1 \quad \forall p \in F, j \in J, s \in S \tag{43}$$

$$\sum_{i \epsilon N} W_{pji}^{s} \geq 1 \quad \forall p \in F, j \in J, s \in S \tag{44}$$

$$\sum_{o \in O} T_{pjo}^{s} \leq 1 \quad \forall p \in F, j \in J, s \in S \tag{45}$$

$$\sum_{o \in O} T_{pjo}^{s} \geq 1 \quad \forall p \in F, j \in J, s \in S \tag{46}$$

Equations A6, A8–A10, A12 and A15–A19.

4.2.2 The dual subproblem

The dual subproblem, denoted as $\mathrm{BSW}\left(x, y|\widehat{U}, \widehat{V}\right)$, is employed to generate Benders cuts for the master problem. To formulate the dual problem, the dual variables π_{hfs}^{1}, π_{hfs}^{2}, π_{jfs}^{3}, π_{ifs}^{4}, π_{ifs}^{5}, π_{jfs}^{6}, π_{ijfps}^{7}, π_{js}^{8}, π_{pjs}^{9}, π_{pjs}^{10}, π_{jfs}^{11}, π_{pjs}^{12}, π_{pjs}^{13}, π_{ifs}^{14}, π_{ifs}^{15}, π_{pjfs}^{16}, π_{js}^{17} and π_{ks}^{18} the dual problem for Constraints (A1–A19) is presented, respectively. In light of these variables, the dual problem BSF (π^{1}, π^{2}, π^{3}, π^{4}, π^{5}, π^{6}, π^{7}, π^{8}, π^{9}, π^{10}, π^{11}, π^{12}, π^{13}, π^{14}, π^{15}, π^{16}, π^{17}, $\pi^{18}|\hat{U}, \hat{V}$) will be as follows:

$$\begin{aligned} \max \sum_{i \in N} \sum_{f \in F} \sum_{s \in S} (-\pi_{ifs}^{1} + \pi_{ifs}^{2}) - \sum_{i \in I} \sum_{f \in F} \sum_{s \in S} \left(-\pi_{ifs}^{4} + \pi_{ifs}^{5}\right) - \sum_{p \in F} \sum_{j \in J} \sum_{s \in S} \left(-\pi_{pjs}^{12} + \pi_{pjs}^{13}\right) \\ - \sum_{p \in F} \sum_{j \in J} \sum_{s \in S} \left(-\pi_{ifs}^{14} + \pi_{ifs}^{15}\right) - \sum_{j \in J} \sum_{s \in S} \left(\pi_{js}^{17} \sum_{e \in E} \sum_{j \in J} \beta_{j}^{e} \widehat{U}_{j}^{e}\right) - \sum_{k \in R} \sum_{s \in S} \left(\pi_{ks}^{18} \sum_{l \in L} e_{k}^{l} \widehat{V}_{k}^{l}\right) \end{aligned} \tag{47}$$

s.t:

$$-\pi_{ifs}^{1} + \pi_{ifs}^{2} \leq \rho^{s} w^{r} rs_{hfv}^{r} \alpha_{fi} + cs_{hfv} \alpha_{fi + w^{r} rh_{hvj}^{r}} \quad \forall i, j, f, p, r, h, v, s \tag{48}$$

$$-\pi_{jfs}^{3}\beta_j^e-\pi_{ifs}^{4}+\pi_{ifs}^{5}-\pi_{jfs}^{6}-\pi_{js}^{17}\alpha_{fi}v_f\le\rho^s w^r rp_{fj}^r\alpha_{fi}\alpha_{fi}+cp_{fij}\alpha_{fi}\quad\forall i,j,f,p,r,s$$

$$-\pi_{jfs}^{6}-\pi_{js}^{8}e_k^l-\pi_{jfs}^{11}-\pi_{ifs}^{14}+\pi_{ifs}^{15}-\pi_{ks}^{18}\beta_j^e\le\rho^s w^r rt_{fijk}^r e_k^l+\rho^s(cn_{fjk}+cm_{fki})\quad\forall i,j,f,r,k,l,e,s \tag{49}$$

$$-\pi_{pjs}^{9}+\pi_{pjs}^{10}-\pi_{pjfs}^{16}\le\rho^s w^r rc_{pi}^r+\rho^s ct_{pgj}\quad\forall i,j,f,p,g,r,s \tag{50}$$

$$-\pi_{pjs}^{12}+\pi_{pjs}^{13}-\pi_{pjfs}^{16}\le\rho^s w^r rd_{po}^r+\rho^s co_{po}\quad\forall j,f,p,r,o,s$$

$$\begin{aligned}&\pi_{hfs}^{1},\pi_{hfs}^{2},\pi_{jfs}^{3},\pi_{ifs}^{4},\pi_{ifs}^{5},\pi_{jfs}^{6},\pi_{ijfps}^{7},\pi_{js}^{8},\pi_{pjs}^{9},\pi_{pjs}^{10},\\&\pi_{jfs}^{11},\pi_{pjs}^{12},\pi_{pjs}^{13},\pi_{ifs}^{14},\pi_{ifs}^{15},\pi_{pjfs}^{16},\pi_{js}^{17},\quad\text{and}\quad\pi_{ks}^{18}\ge 0\quad\forall i,j,f,p,h,k,s\end{aligned} \tag{51}$$

The primary Benders problem can be formulated as follows:

$$\min_{U,K} z \tag{52}$$

s.t:

$$\begin{aligned}z\ge\ &\max\sum_{i\in N}\sum_{f\in F}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{1a'}+\hat{\pi}_{ifs}^{2a'}\right)-\sum_{i\in I}\sum_{f\in F}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{4a'}+\hat{\pi}_{ifs}^{5a'}\right)\\&-\sum_{p\in F}\sum_{j\in J}\sum_{s\in S}\left(-\hat{\pi}_{pjs}^{12a'}+\hat{\pi}_{pjs}^{13a'}\right)-\sum_{p\in F}\sum_{j\in J}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{14a'}+\hat{\pi}_{ifs}^{15a'}\right)\\&-\sum_{j\in J}\sum_{s\in S}\left(\hat{\pi}_{js}^{17a'}\sum_{e\in E}\sum_{j\in J}\beta_j^e\hat{U}_j^e\right)-\sum_{k\in R}\sum_{s\in S}\left(\hat{\pi}_{ks}^{18a'}\sum_{l\in L}e_k^l\hat{V}_k^l\right)\quad\forall a'\\&=1,\dots,\acute{A}\end{aligned} \tag{53}$$

$$\begin{aligned}\mathcal{H}+&\max\sum_{i\in N}\sum_{f\in F}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{1b'}+\hat{\pi}_{ifs}^{2b'}\right)-\sum_{i\in I}\sum_{f\in F}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{4b'}+\hat{\pi}_{ifs}^{5b'}\right)\\&-\sum_{p\in F}\sum_{j\in J}\sum_{s\in S}\left(-\hat{\pi}_{pjs}^{12b'}+\hat{\pi}_{pjs}^{13b'}\right)-\sum_{p\in F}\sum_{j\in J}\sum_{s\in S}\left(-\hat{\pi}_{ifs}^{14b'}+\hat{\pi}_{ifs}^{15b'}\right)\\&-\sum_{j\in J}\sum_{s\in S}\left(\hat{\pi}_{js}^{17b'}\sum_{e\in E}\sum_{j\in J}\beta_j^e\hat{U}_j^e\right)-\sum_{k\in R}\sum_{s\in S}\left(\hat{\pi}_{ks}^{18b'}\sum_{l\in L}e_k^l\hat{V}_k^l\right)\le 0\quad\forall b'\\&=1,\dots,\acute{B}\end{aligned} \tag{54}$$

$$\sum_{e\in E}U_j^e\le 1\quad\forall j\in J \tag{55}$$

$$\sum_{l\in L}V_k^l\le 1\quad\forall k\in K \tag{56}$$

Finally, the process involves first solving the main problem without any cuts. Subsequently, the solution of the main problem is transferred to the subproblem, which is also solved. If the subproblem is infeasible, and the solution of the dual problem is unbounded, then a new direction is determined from the dual problem, a cut is generated, and it is incorporated into the main problem. On the other hand, if the subproblem is feasible and possesses an optimal solution, an optimal cut is integrated into the main problem using the optimal solutions from the dual subproblem. If the newly acquired solution results in an improved upper bound, the previous upper bound is updated. The process is reiterated until the gap between the upper and lower bounds becomes smaller than a predefined threshold. Algorithm 1 outlines the pseudocode of this proposed methodology.

Algorithm 1 Pseudocode of the Benders algorithm

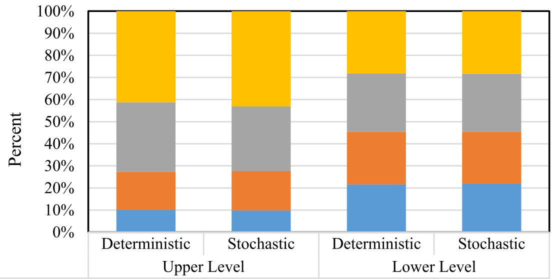
{Initialization}
Set (U, V); |* *initial feasible integer solution* *|
Set $\widehat{U}_{hr} = 0,\ \widehat{V}_{kl} = 0,\ \varepsilon = 0.01,\ LB = -\infty, UB = +\infty$ and $a' = b' = 0$
While ($UB - LB > \varepsilon$) Do
  Solve (*subproblem*)
  If (*Subproblem is Unbounded) then*
  Get unbounded ray π
    Add *feasibility cut (equations* (54))
    to master problem
  Set $b' := b' + 1$;
Else
  Get extreme point π
    Add *feasibility cut equations* (53)
    to master problem
  $a' := a' + 1$;
    $UB := \min\{UB, z \geq$ *equations* (53)
End if
  Solve (*master problem*)
    $LB := \bar{z}$// |* *result of master problem* *|
End while

In our research, Algorithm 1, which includes the pseudocode of the Benders algorithm, was implemented in MATLAB using a system equipped with an i7 processor and 16 GB of RAM. The proposed algorithm was executed considering the conditions and constraints of the model, including Eqs. (53) and (54). The input data from Tables 4 and 5 were utilized for the implementation. The computational results obtained from running the algorithm on these data were thoroughly analyzed and evaluated. These results were then provided in Figs. 4, 5, 6, 7, 8 and 9, demonstrating the outputs and performance metrics of the solution.

5 Calculate the weight associated with SRs in CLSC

The most critical sustainability criteria are economic growth, environmental protection, and social equality (Silvius & Schipper, 2015). In addition to these three pillars, the standard of production and operation is also considered in this research. As organizations are convinced to consider sustainability criteria in their decision-making process, sustainability risks in SC activities have become an important issue.

In this study, sustainable risks are first identified and grouped based on the knowledge of industry experts in PES Company as a case study and based on previous research. PES Company produces polyethylene pipes with 77,000 tons per year production capacity. Then, by reviewing articles in this field and field studies, several questionnaires were used to identify the sub-criteria related to sustainable risks. The questionnaires were sent to experts of the PES Company. To achieve this, we utilized published information from previous research to create a questionnaire with four sustainability risks and 18 sub-criteria, including economic risk, environmental risk,



	Upper Level – Deterministic	Upper Level – Stochastic	Lower Level – Deterministic	Lower Level – Stochastic
Very high demand	76,013	98,013	6,82,84,133	8,64,74,401
High demand	58,126	66,278	6,40,75,829	8,04,36,790
Medium demand	31,861	40,606	5,76,76,402	7,15,37,592
Low demand	18,483	22,319	5,23,47,532	6,71,77,219

Fig. 4 Decisions of the first phase in different scenarios

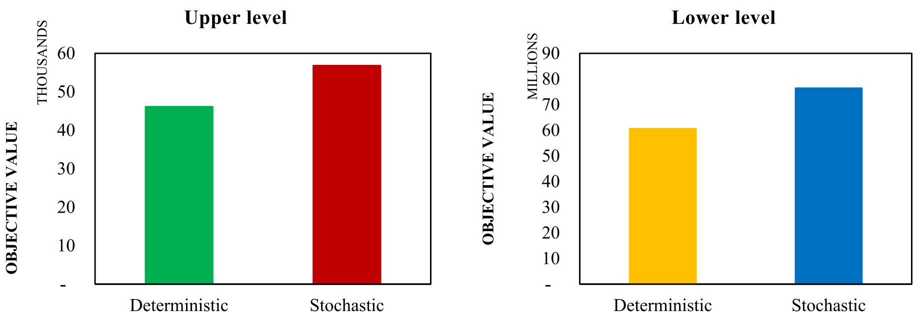
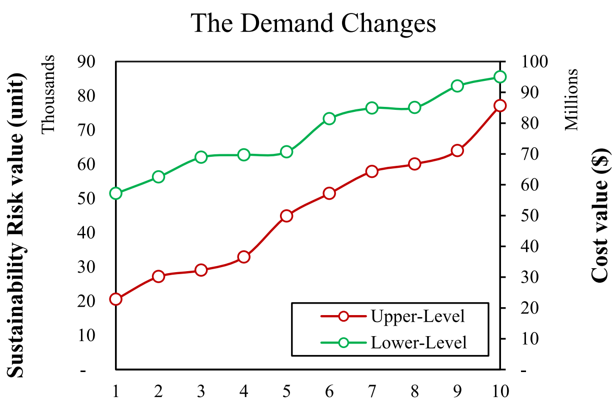


Fig. 5 Results for the objective function values

Fig. 6 Effect of changes in demand



social risk, and operational risk. Each sustainable risk and its related sub-components are categorized in Table 2.

A weighting table of risks and sub-criteria was presented in the second step. Finally, the resulting weight table is proposed to achieve the value of each risk in the upper-level objective function. As a comprehensive decision method, the fuzzy analytic network process (FANP) presents the weight of sustainability risks, sub-criteria, and relative importance

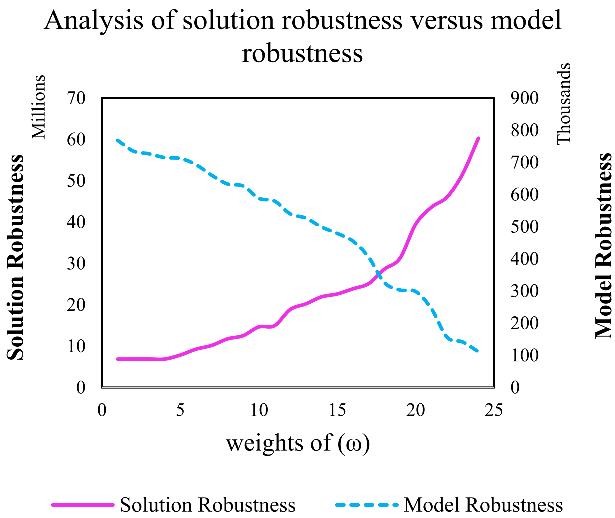


Fig. 7 Sensitivity analysis of proposed model

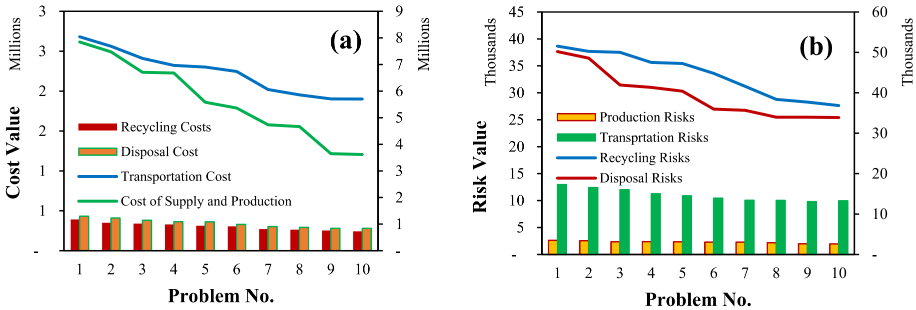


Fig. 8 Result of solving the model

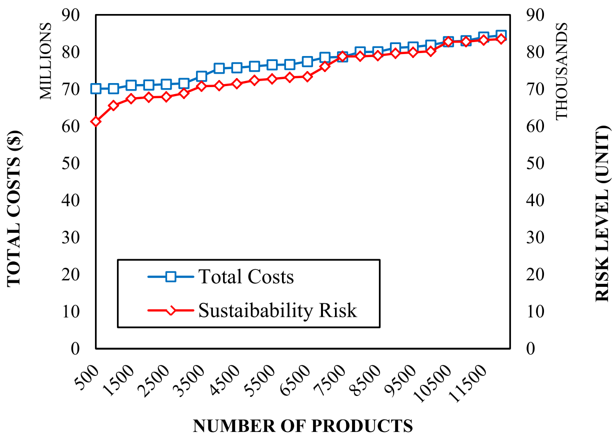


Fig. 9 Model sensitivity analysis based on capacity changes

Table 2 Sustainability risks and sub-criteria

Main criteria	Code	Sub-criteria	References
Economical risks	C1	Price fluctuations	Tang and Musa (2011), Giannakis and Papadopoulos (2016)
	C2	Inflation	Tummala and Schoenherr (2011), Song et al (2017)
	C3	Decreasing market contribute	Afgan and Carvalho (2004)
	C4	Cost of goods	Chowdhury and Quaddus (2021), Wang and Dai (2018)
	C5	Value-added	Delai and Takahashi (2011)
Environmental risks	C6	Air pollution and GHG emissions	Chowdhury and Quaddus (2021), Pattnaik et al. (2021)
	C7	Resource consumption (material, energy, water)	Chowdhury and Quaddus (2021)
	C8	Waste generation	Rao and Holt (2005)
	C9	Eco-design, production and packaging	Chowdhury and Quaddus (2021), , Rao and Holt (2005)
Social risks	C10	Dangerous and unhealthy work location	Wang and Dai (2018), Shafiq et al. (2014), Mani et al. (2016)
	C11	Child labor	Chowdhury and Quaddus (2021), Wang and Dai (2018), Shafiq et al. (2014)
	C12	Failure to fulfill the social commitment	Maloni and Brown (2006)
	C13	Violation of business ethics	Roberts (2003)
	C14	Customer satisfaction	Wang and Dai (2018), Delai and Takahashi (2011)
Operational risks	C15	Material flow risk source	Tang and Musa (2011), Norrman and Jansson (2004)
	C16	Production risk	Tang and Musa (2011), Handfield et al. (1999), Khan et al. (2008), Peck (2005)
	C17	Logistic and delivery risk	Tang and Musa (2011), Bovet (2006)
	C18	Demand (volatility/seasonality) risk	Tang and Musa (2011), Bovet (2006)

among them using pairwise comparisons (Saaty, 1996). This method is very suitable in cases where the dependency between the criteria for selecting possible options is high. FANP simply determines the relationships between the criteria. In this method, the matrix of pairwise comparisons between the criteria in each row is completed using fuzzy triangular numbers. In this method, the parameter values are obtained in fuzzy triangular numbers and are calculated as fuzzy.

In a pairwise comparison of sustainability risks, the decision-maker (expert) may use fuzzy triangular numbers to determine the degree of priority of the risk. In other words, the decision-maker may not express a specific number as a preference when comparing some of the risks. That is why a fuzzy—spectrum can be used for fuzzy triangular numbers instead of the logical $\widetilde{19}$ spectrum. When risk i is compared with risk j,$\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$, it indicates equal preferences among the compared risks, low preference i over j, stronger preference i over j, much stronger preference, and absolute preference i over j. The pairwise comparison matrix is formed using fuzzy triangular numbers (l, m, u) to evaluate the decision-maker's choices. The fuzzy triangular number matrix can be shown as follows.

$$\tilde{A} = \begin{bmatrix} (a_{11}^l, a_{11}^m, a_{11}^u) & (a_{12}^l, a_{12}^m, a_{12}^u) & \cdots & (a_{1n}^l, a_{1n}^m, a_{1n}^u) \\ (a_{21}^l, a_{21}^m, a_{21}^u) & (a_{22}^l, a_{22}^m, a_{22}^u) & \cdots & (a_{2n}^l, a_{2n}^m, a_{2n}^u) \\ \vdots & \vdots & \vdots & \vdots \\ (a_{m1}^l, a_{m1}^m, a_{m1}^u) & (a_{m2}^l, a_{m2}^m, a_{m2}^u) & \cdots & (a_{mn}^l, a_{mn}^m, a_{mn}^u) \end{bmatrix} \tag{57}$$

In this matrix, the value $[i, j]$ signifies the relative importance of the ith element (row) in comparison with the jth element (column). If this matrix represents a pairwise comparison matrix, it is assumed that the elements in this matrix are inversely related to the original diameters. Consequently, the value α can be assigned to the element $[i, j]$. Therefore, the pairwise comparison matrix takes the following form:

$$\tilde{A} = \begin{bmatrix} (1, 1, 1) & (a_{12}^l, a_{12}^m, a_{12}^u) & \cdots & (a_{1n}^l, a_{1n}^m, a_{1n}^u) \\ \left(\frac{1}{a_{12}^U}, \frac{1}{a_{12}^m}, \frac{1}{a_{12}^L}\right) & (1, 1, 1) & \cdots & (a_{2n}^l, a_{2n}^m, a_{2n}^u) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{a_{1n}^u}, \frac{1}{a_{1n}^m}, \frac{1}{a_{1n}^l}\right) & \left(\frac{1}{a_{2n}^u}, \frac{1}{a_{2n}^m}, \frac{1}{a_{2n}^l}\right) & \cdots & (1, 1, 1) \end{bmatrix} \tag{58}$$

There are many methods to estimate fuzzy weights with $\tilde{w}_i$ matrix $\tilde{A}$ with an approximate value $\tilde{a}_{ij} \approx \tilde{w}_i/\tilde{w}_j$ so that the value $(\tilde{w}_i = (w_i^l, w_i^m, w_i^u)$ is obtained for $i = 1, 2, \ldots, n$. One of the methods employed in this study is the logarithmic least-squares method, as established by Chen et al. (1992), serving as the foundation for the calculation of fuzzy weights. Using this method, triangular fuzzy weights can be computed for various factors, such as criteria and options, as elucidated by Ramík (2006). The logarithm of least-squares method for calculating the fuzzy weights is shown as follows:

$$\tilde{w}_k = (w_k^l, w_k^m, w_k^u) \quad k = 1, 2, 3, \ldots, n \tag{59}$$

If

$$w_k^s = \frac{\left(\prod_{j=1}^n a_{kj}^s\right)^{1/n}}{\sum_{i-1}^n \left(\prod_{j=1}^n a_{kj}^m\right)^{1/n}}, \quad s \in \{l, m, u\} \tag{60}$$

This method first obtains triangular numbers based on fuzzy numbers and uses the geometric mean for all risks to get the corresponding fuzzy numbers. We bring the sum of the standard of the fuzzy numbers and use the following formula.

$$\sum_{i-1}^{n}\left(\prod_{j=1}^{n} a_{kj}^{m}\right)^{1/n} \tag{61}$$

And then, we divide all the numbers obtained from the geometric mean by the above sum and use the following formula:

$$w_k^s = \frac{\left(\prod_{j=1}^{n} a_{kj}^{s}\right)^{1/n}}{\sum_{i-1}^{n}\left(\prod_{j=1}^{n} a_{kj}^{m}\right)^{1/n}}, \quad s \in \{l, m, u\} \tag{62}$$

It should be noted that the two matrices obtained, namely the matrices for each criterion and the matrix obtained from the above method, should be used using the logarithmic, least-squares method to get the final weights. Finally, the weights obtained for sustainable risks and sub-criteria were obtained in Table 3. In the next step, the weights obtained are applied at the upper level of the model.

5.1 Computational results

In this part of the paper, the proposed optimization model is analyzed based on the weights obtained in the previous section and the data collected in Tables 4 and 5. For this purpose, first, a numerical example is designed in a minimal size; the model was solved using the exact solution method in both deterministic and stochastic form. In addition, the sensitivity analysis was performed on various parameters of the model.

We have considered different scenarios for the amount of demand. These scenarios are deemed to be based on the levels set for the amount of demand. In this study, four categories are considered for scenarios including (low, medium, high, and very high) demand, each with a probability. The event is related to itself. Manufacturers put production levels and storage capacity strategies on the plan based on these scenarios. Table 6 shows the 12-point customer demand.

6 Model solving and data analysis

This section aims to address the proposed model using the data presented in Tables 3, 4, 5 and 6. Given the uncertainty associated with certain parameters, particularly demand, the model is analyzed in light of multiple scenarios and their associated probability values. Figure 4 provides a comparison of the initial decisions generated by both deterministic and stochastic models. Notably, it becomes evident that altering the probability of each scenario's occurrence leads to substantial variations in the objective function values. Moreover, a

Table 3 Weights obtained for risks and sub-criteria

Main criteria	Weight	Code	Total weight	Weight in main criteria
Economical risks	0.3974	C1	0.0996	0.2593
		C2	0.1045	0.3134
		C3	0.0965	0.2156
		C4	0.0545	0.095
		C5	0.0615	0.1167
Environmental risks	0.2674	C6	0.0825	0.356
		C7	0.0506	0.301
		C8	0.0435	0.162
		C9	0.0445	0.181
Social risks	0.2507	C10	0.0575	0.2315
		C11	0.0315	0.1716
		C12	0.0775	0.3832
		C13	0.0415	0.1265
		C14	0.0305	0.0872
Operational risks	0.0845	C15	0.0345	0.3336
		C16	0.0325	0.2679
		C17	0.0255	0.1874
		C18	0.0295	0.2111

Table 4 Information on the number of locations

Type of product	The number of consumers	The number of factories	The number of warehouses	The number of disposal locations
14	55	4	22	5

noticeable discrepancy is observed between the solutions obtained when solving the model in a deterministic state as compared to those obtained in the stochastic state.

Table 7 shows the optimal results obtained for both levels of the problem. In the obtained results, the optimal point for the problem is the optimal point between the two levels. But this does not mean the Pareto border (Safaei et al., 2018). Note that some variables influence bi-level models at each level, which justifies the difference between the results obtained with the Pareto boundary in multi-objective problems. In this particular case, the optimal point for both levels of the model tends to be the upper level of the problem. These indicate the effectiveness of the final optimal result of sustainable risks.

Figure 5 illustrates the optimal values derived from the bi-level model. Based on the scenarios, it becomes evident that the greater the volume of products manufactured, the more substantial the sustainability risks, which also lead to an increase in the number of returned products and their recycling. Figure 5 further contrasts the disparities between the optimal solutions attained in both deterministic and stochastic approaches for each level of the proposed model. Notably, it is observed that the stochastic solution results in a 26% increase in total costs. This increase is attributed to the consideration of demand in various

Table 5 Values related to the problem parameters

Parameters	Surfaces	Parameters	Surfaces
cf_j^e	~ U (7000000, 9000000)	rs_{hfv}^r	~ U (30, 55)
cl_k^l	~ U (40000, 60000)	rp_{fj}^r	~ U (40, 70)
cs_{hfv}	~ U (5, 9)	rh_{hvj}^r	~ U (20, 30)
cp_{fij}	~ U (1, 1.8)	rt_{fijk}^r	~ U (20, 30)
ch_{hvj}	~ U (2, 2.5)	rc_{pi}^r	~ U (20, 30)
cn_{fjk}	~ U (2, 2.5)	rd_{po}^r	~ U (70, 90)
cm_{fki}	~ U (1.5, 2)	v_f	~ U (10, 25)
ct_{pj}	~ U (1, 1.5)	π_f	~ U (.06, .08)
co_{po}	~ U (3, 5)	β_j^e	~ U (150, 250)
α_{fi}	~ U (300, 500)	e_k^l	~ U (65, 85)

scenarios. Additionally, at the upper level of the model, it is noticeable that the extent of sustainability risks in the stochastic model is 23% higher than in the deterministic case.

Due to uncertainty in customer demand, production centers and warehouses may face capacity shortages. Depending on the occurrence of each scenario indicated by ρ^s, different values are obtained for each level of the problem. It should be noted that this amount must be positive, which means that the amount received for the cost cannot be negative. Moreover, the negative risk level is not allowed. However, the negative rate for capacity is significant. It means there is insufficient capacity in the production centers, or the amount of product transferred exceeds the maximum storage capacity. Figure 6 shows the changes in cost and risk in each scenario.

6.1 Sensitivity analysis model

Typically, in robust models, the degree of adaptability of the model is assessed based on the weight assigned to stochastic parameters. This is done to evaluate the proposed model and method, which demonstrates the effectiveness of the robust model in withstanding various problem conditions. Figure 7 presents sensitivity analysis related to model robustness and solution robustness, aiming to assess the robust model's performance. This analysis explores the value of "w" in different scenarios, as depicted in Fig. 7. As "w" increases, solution robustness also increases. However, a declining trend is observed in model robustness. The contrasting behavior of model robustness and solution robustness underscores the substantial impact of the number of demanded products on sustainability risks and total costs. In essence, to reduce sustainability risks, it becomes necessary to allocate additional costs to accommodate fluctuations in demand.

Figure 8 provides the model's result based on the sustainability risk and total costs function. Figure 8a shows that the costs of raw material supply, production, transportation and distribution, recycling, and defective product disposal were reduced by ten repetitions. Moreover, Fig. 8a shows that the transportation cost was higher than the waste production cost, which decreased significantly during ten repetitions. On the other hand, as shown in Fig. 8b, the risks of production, transportation, recycling, and disposal of defective products also decreased over ten repetitions of the problem. Comparing the decreasing trend in Fig. 8a and b, it can be seen that the cost reduction process is relatively faster than the risk

Table 6 Amount of demand in different scenarios

Possibility	The volume of demand												Scenarios
	1	2	3	4	5	6	7	8	9	10	11	12	
0.25	43	40	42	36	43	44	36	38	31	41	44	32	Very high demand
0.45	41	36	36	30	34	40	36	31	30	32	37	31	High demand
0.25	36	31	33	21	32	34	33	27	22	27	26	30	Medium demand
0.05	25	28	32	20	30	25	24	24	20	25	23	28	Low demand

Table 7 Numerical results obtained from solving the proposed model

Models	Upper-level objective	Lower-level objective
Leader's model	46,121	60,595,974
Follower's model	785,420,160	469,275
Bi-level model	864,202,766	683,438

reduction process. Therefore, it can be concluded that the proposed model has a more significant impact on cost optimization (lowest level of the model). This, while the decreasing trend of the risk level, also indicates the model's efficiency in this area.

Figure 9 shows the model's sensitivity to capacity change in factories and warehouses. As shown, changing capacity affects total cost and suitability risks, especially when capacity is less than 6,500 products. As demand increases, producers increase production capacity, increasing costs and creating sustainability risks. Obviously, in the event of a lack of capacity for factories and warehouses, we will face lost demand, which will reduce the performance of our CLSC.

6.2 Managerial insights

As obtained from the data analysis, this study provided an efficient model that, in addition to the model's resilience to various uncertain conditions and data, can significantly reduce the total costs and sustainability risks related to CLSC activities. The results of solving the model lead to valuable management insights: (i) manufacturers to consider sustainability risks in their supply chain network more than ever before. According to the results, among the sustainable risks, economic risks are the most important compared to other sustainability risks in CLSC. However, according to the weights obtained, environmental risks are in second place after economic risks. (ii) On the other hand, by modeling the results of this research, managers may consider appropriate decisions to balance the capacity of factories and warehouses despite demand fluctuations in different scenarios. According to the data obtained from Fig. 9, it is found that the right decisions on the correct capacity utilization will reduce the total cost by 16%, which is a significant figure. (iii) Indeed, deterministic models applied in practical problems often limit the model's adaptability in the face of uncertain real-world conditions. Hence, in the proposed model, taking into account various scenarios and uncertain demand proves to be a valuable approach for addressing this issue. (iv) Using a bi-level model helps managers optimize the CLSC for polyethylene products by considering two concerns (total cost and sustainability risks). (v) Finally, policymakers play a critical role in driving the adoption of CLSCs and promoting sustainability in the industry. They can establish regulations and incentives to encourage suppliers and manufacturers to integrate sustainability considerations into their supply chain operations. These policies can include measures such as tax credits for using recycled materials, penalties for excessive waste generation and GHG emissions, and subsidies for implementing green technologies.

7 Conclusion

In this study, our objective was to comprehensively address sustainability risks, including economic, environmental, social, and operational risks, which aligns with previous studies such as Giannakis and Papadopoulos (2016), Valinejad and Rahmani (2018), Xu et al. (2019), and Chowdhury and Quaddus (2021). However, we also extended the scope by considering operational risks, which had not been previously addressed in the literature. Furthermore, our research aimed to incorporate two levels of concern within the CLSC framework. At the upper level, we focused on sustainability risks, while at the lower level, we emphasized operating costs. This approach is consistent with Lotfi et al. (2021), who also recognized the significance of considering two levels of concern. Additionally, we took into account the return rate of products in the CLSC network, which is in line with the findings of Ghayebloo et al. (2015), Huang et al. (2016), Valinejad and Rahmani (2018), Fazli-Khalaf et al. (2021), Ghasemzadeh et al. (2021), and Rajak et al. (2022). By incorporating the return rate, we aimed to capture the complexities and uncertainties associated with product returns, further enhancing the applicability of our research.

In this research, to convert the proposed bi-level model to the single-level model and create an optimized space, the combined KKT condition method and the Benders decomposition approach were used as a solution. After solving the model in two deterministic and stochastic cases by considering different scenarios, the efficiency of the proposed model was examined by some analyzes. The results of sustainability risk assessment based on a questionnaire and expert opinion showed that economic risks have the most significant impact among other risks. By entering these results at the upper level of the model, solving the bi-level model showed that the model in different repetitions reduces the risks of stability and total cost. Therefore, considering the possibility of a crisis and its effects on the SC network may be intriguing for future researchers. The study also assumed that all customer demand would be covered. In future research, the scarcity of excess demand may be considered. Government policy formulation, such as financial incentives or penalties for supply violations, is also interesting in SC-related issues.

In addition to the contributions made in this study, several future research avenues and implications emerge. Firstly, considering the possibility of crises and their impact on the SC network would be an intriguing area for further investigation. Future research could explore strategies for managing and mitigating the effects of unforeseen disruptions in the CLSC. Secondly, one significant area of exploration lies in the potential role of digital transition issues within the context of CLSCs. As digital technologies continue to advance and reshape various industries, their integration into SC operations offers new opportunities and challenges (Abbate et al., 2022). Future research endeavors could explore the ways in which digitalization and emerging technologies, such as the Internet of Things (IoT), blockchain, artificial intelligence (AI), and data analytics, can be harnessed to augment the sustainability and efficiency of closed-loop supply chains (CLSCs).

This includes exploring the application of these technologies in areas such as traceability, real-time monitoring, inventory management, demand forecasting, reverse logistics optimization, and waste tracking.

Appendix 1

$$\begin{aligned}\min Z1 = \sum_{s} \rho^{s}(\mathcal{A}^{s} + \mathcal{B}^{s} + \mathcal{C}^{s} + \mathcal{D}^{s} + \varepsilon^{s} + \mathcal{F}^{s}) \\ + \lambda_1 \sum_{s} \rho^{s}([\mathcal{A}^{s} + \mathcal{B}^{s} + \mathcal{C}^{s} + \mathcal{D}^{s} + \varepsilon^{s} + \mathcal{F}^{s}] \\ - \sum_{s'} \rho^{s'}[\mathcal{A}^{s} + \mathcal{B}^{s} + \mathcal{C}^{s} + \mathcal{D}^{s} + \varepsilon^{s} + \mathcal{F}^{s}] + 2\theta_1^{s}) + \omega \sum_{i}\sum_{s} \rho^{s} \cdot \delta_{1i}^{s},\end{aligned} \tag{A1}$$

$$\begin{aligned}\min Z2 = \sum_{s} \rho^{s}(\mathcal{H} + \mathcal{K}^{s} + \mathcal{L}^{s} + \mathcal{M}^{s} + \mathcal{N}^{s} + \mathcal{O}^{s}) + \lambda_2 \sum_{s} \rho^{s}\left(\left[\mathcal{H} + \mathcal{K}^{s} + \mathcal{L}^{s} + \mathcal{M}^{s} + \mathcal{N}^{s} + \mathcal{O}^{s}\right]\right. \\ \left. - \sum_{s'} \rho^{s'}\left[\mathcal{H} + \mathcal{K}^{s} + \mathcal{L}^{s} + \mathcal{M}^{s} + \mathcal{N}^{s} + \mathcal{O}^{s}\right] + 2\theta_2^{s}\right) + \omega \sum_{i}\sum_{s} \rho^{s}.\delta_{2i}^{s}\end{aligned} \tag{A2}$$

s.t.

$$\mathcal{A}^{s} + \mathcal{B}^{s} + \mathcal{C}^{s} + \mathcal{D}^{s} + \mathcal{E}^{s} + \mathcal{F}^{s} - \sum_{s} \rho^{s}(\mathcal{A}^{s} + \mathcal{B}^{s} + \mathcal{C}^{s} + \mathcal{D}^{s} + \mathcal{E}^{s} + \mathcal{F}^{s}) + \theta_1^{s} \geq 0 \tag{A3}$$

$$\mathcal{H} + \mathcal{K}^{s} + \mathcal{L}^{s} + \mathcal{M}^{s} + \mathcal{N}^{s} + \mathcal{O}^{s} - \sum_{s} \rho^{s}(\mathcal{H} + \mathcal{K}^{s} + \mathcal{L}^{s} + \mathcal{M}^{s} + \mathcal{N}^{s} + \mathcal{O}^{s}) + \theta_2^{s} \geq 0 \tag{A4}$$

$$\sum_{v \in V} X_{hfv}^{s} = 1 \quad \forall h \in H, f \in F, s \in S \tag{A5}$$

$$\sum_{i \epsilon N}\sum_{e \in E} Y_{fij}^{s}\beta_j^{e} \leq \sum_{h \in H}\sum_{v \in V} X_{hfv}^{s}\alpha_{fi} \quad \forall j \in J, f \in F, s \in S \tag{A6}$$

$$\sum_{j \in J} Y_{fij}^{s} = 1 \quad \forall i \in N, f \in F, s \in S \tag{A7}$$

$$\sum_{i \in N} Y_{fij}^{s} - \sum_{k \epsilon K} Q_{fjk}^{s} = 0 \quad \forall j \in J, f \in F, s \in S \tag{A8}$$

$$\pi_f Y_{fij}^{s} \geq M.W_{pji}^{s} \quad \forall i \in N, j \in J, f \in F, p \in F, s \in S \tag{A9}$$

$$\sum_{k \in K}\sum_{f \in F}\sum_{l \in L} e_k^{l} Q_{fjk}^{s} \leq \sum_{i \in N}\sum_{f \in F}\sum_{e \in E} \beta_j^{e} Y_{fij}^{s} \quad \forall j \in J, s \in S \tag{A10}$$

$$\sum_{i \epsilon N} W^{s}_{pji} = 1 \quad \forall p \in F, j \in J, s \in S \tag{A11}$$

$$\sum_{k \epsilon K} Q^{s}_{fjk} \leq \sum_{i \epsilon N} Y^{s}_{fij} \quad \forall j \in J, f \in F, s \in S \tag{A12}$$

$$\sum_{o \in O} T^{s}_{pjo} = 1 \quad \forall p \in F, j \in J, s \in S \tag{A13}$$

$$\sum_{k \in K} Q^{s}_{fjk} = 1 \quad \forall i \in N, f \in F, s \in S \tag{A14}$$

$$\sum_{i \epsilon N} W^{s}_{pji} + \sum_{o \in O} T^{s}_{pjo} \leq \sum_{k \in K} Q^{s}_{fjk} \quad \forall p \in F, j \in J, f \in F, s \in S \tag{A15}$$

$$\sum_{i \in N} \sum_{f \in F} \alpha_{fi} v_f Y^{s}_{fij} \leq \sum_{e \in E} \beta^{e}_{j} U^{e}_{j} \quad \forall j \in J, s \in S \tag{A16}$$

$$\sum_{j \in J} \sum_{e \in E} \sum_{f \in F} \beta^{e}_{j} Q^{s}_{fjk} \leq e^{l}_{k} V^{l}_{k} \quad \forall k \in K, s \in S \tag{A17}$$

$$X^{s}_{hfv} \geq 0, Y^{s}_{fij} \geq 0, Y^{s}_{fij} \geq 0, Q^{s}_{fjk} \geq 0, W^{s}_{pji}, T^{s}_{pjo} \geq 0 \geq 0 \forall i \in N, j \in J, f \in F, p \in F, k \in K \quad \text{and} \quad s \in S \tag{A18}$$

$$U^{e}_{j}, V^{l}_{k} \in (0, 1) \quad \forall k \in K \quad \text{and} \quad l \in L \tag{A19}$$

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