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A robust mixed flexible-possibilistic programming approach for multi-objective closed-loop green supply chain network design

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Abstract
In recent years, due to governmental legislation, environmental groups' pressures, customer green expectation, etc., closed-loop green supply chains have gained paramount consideration. Accordingly, this study develops a novel multi-objective mixed integer nonlinear programming model for a closed-loop green supply chain network design problem. The proposed model aims to minimize the total costs, total CO_2 emissions, and robustness costs in both forward and reverse directions, simultaneously. To cope with flexible constraints and epistemic uncertainty in the model's parameters, a robust flexible-possibilistic programming approach is tailored. The model is solved using an efficient interactive solution approach, in which, the presented model is analyzed under various carbon emission mechanisms to assess the influence of these mechanisms on the achieved solution. An illustrative example in the copier industry is also provided to validate the applicability of the presented optimization model. Numerical results indicate the superiority of the carbon cap-and-trade policy in most of the cases.

Keywords Network design · Carbon emission mechanisms · Closed-loop green supply chain · Mixed flexible-possibilistic programming · Robust programming

1 Introduction

A supply chain (SC) network typically incorporates a set of suppliers, manufacturers, and distribution centers as the nodes and a number of links between these facilities as the arcs of the network. Determining the location, number, capacity, and the level of technology in the network's facilities alongside the amount of material flow traversing

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the network are among the main typical strategic (long-term) and tactical (mid-term) decisions which significantly influence the SCs' total performance (Ghahremani-Nahr et al. 2019).

A typical SC includes both forward and reverse flows. The goal of forward SC is defined as receiving raw materials, changing them into final goods and dispatching finished goods to customer zones (Babazadeh et al. 2013). However, in recent decades, several firms have started to focus on used materials and products, because of governmental legislations, customers becoming more aware of environmental issues, waste reduction, growing disposal costs, and recovery programs (Fleischmann et al. 2009). This issue has a paramount importance in electronics equipment (e.g., copier industry) where using the valuable/usable parts of the used products in the remanufacturing process could reduce 40–60% of the total manufacturing costs (Sane Zerang et al. 2016; Savaskan et al. 2004). Indeed, a reverse SC can be defined as an evolution of conventional forward SC which includes all the SC exercises essential for reintroducing valued-objects, which are not proper for executing their main role anymore, into certain recovery frameworks for the end of either recovering value or appropriate discarding (Fleischmann et al. 2009).

Accordingly, a closed-loop supply chain network (CLSCN), as a well-known extension of the classical one, incorporates both forward and reverse logistics (Özceylan and Paksoy 2013). In the forward logistics, distribution centers dispatch final products to customer zones, to meet their demands while in the reverse logistics, activities such as disassembling for reuse, disposal or recovery or sorting are carried out. Integrating these activities can enhance the service level of customers, increase enterprise competence, provide a green image, and also decrease the production costs (Demirel and Gökçen 2008).

Supply chain exercises are the significant source of greenhouse gas emissions (GHGs). There are ever-increasing agreements on this fact that environmental impacts are leading to main changes to both environmental and ecological frameworks. Also, governmental organizations around the world are under an ever-increasing pressure to limit these influences. These restrictions that control the GHGs, specifically CO_2 emissions, are turning into growing concern, and enterprises are being encouraged to consider these issues in their SC management activities (PAGELL and WU 2009; Benjaafar et al. 2013; Ding et al. 2016). Among developed mechanisms to control GHGs, carbon tax/cap/cap-and-trade/offset mechanisms are the main carbon emission mechanisms that have been addressed in the recent studies (Benjaafar et al. 2013; Fareeduddin et al. 2015; Jin et al. 2014; Palak et al. 2014; Waltho et al. 2019).

On the other hand, data uncertainty (e.g., epistemic uncertainty in customers demand, unit costs, product quality, etc.) arising from considerable fluctuations of these data over a long decision horizon is one of the most critical issues in the real-world SC network design problems (Talaei et al. 2016). To contend with different types of uncertainty, different uncertainty programming approaches have been introduced, among them, fuzzy programming (FP), stochastic programming (SP), and robust optimization (RO) are the most applied ones. When randomness is the main source of uncertainty in the input coefficients of a decision model and there are enough historical data to estimate their probability distributions reliably, SP approach is a suitable candidate to cope with such uncertain data. However, in the majority of real cases, as there is not enough historical data, obtaining the exact random distribution of uncertain input data is difficult. Also, some cases may deal with elasticity (softness) in constraints or/and flexibility on the goals' target values. FP method can deal with both the epistemic uncertainty in input data and soft constraints using the two well-known categories of FP approach, i.e., the possibilistic and flexible programming approaches, respectively (Mousazadeh et al. 2018). Finally, RO approach provides risk-averse methods to cope with random uncertainty when the distributional information about random data is not available (Pishvaee et al. 2012).

Undoubtedly, ignoring uncertainty in long-lasting (strategic) decisions, e.g., SCND will impose a high risk to the system. Accordingly, designing a CLSCN under uncertainty of critical input parameters as well as flexibility in goals' target values and/or elasticity in constraints seems to be necessary for obtaining a robust solution.

Now, considering the aforementioned facts, designing a robust closed-loop green SC network under epistemic uncertainty of input data and the presence of flexible constraints along with considering various emission policies are among the main research challenges/questions that are addressed in this study. Furthermore, the optimal location and capacity of the SC's facilities, the optimal quantity of produced/remanufactured, and disassembled products in the manufacturing/remanufacturing centers, and DCs, respectively, and finally the optimal amount of products flow in the designed network are among the main sub-challenges/questions which must be answered by the developed optimization model. Accordingly, the goal of this study is to develop an optimization framework for an integrated forward/reverse SC network design problem under uncertainty. The concerned network includes two echelons namely, manufacturing centers (MCs), and warehouses (WHs) in the forward direction and two echelons namely, disassembling centers (DCs) and remanufacturing centers (RCs) in the reverse direction. The first objective function (OF) tries to minimize the total costs, while the second one tends to minimize the total CO_2 emission. Also, the third objective aims at minimizing the robustness cost in both forward and reverse directions, simultaneously. It is noteworthy to say that since the robustness costs are virtual costs (i.e., they are not a real part of operating costs, which consist of real costs such as fixed costs, transportation costs.), logically they cannot be summed in a single OF in a line with other operating costs. Hence, this OF is defined separately to cope with deficiencies of this undesirable integration (Mousazadeh et al. 2018). Notably, a comprehensive discussion regarding the third OF presented in Sect. 4.

Also, some input data (e.g., fixed establishment costs, saving costs, transportation costs, the capacities of facilities, and demands) are tainted with epistemic uncertainty because of the unavailability of required objective data to estimate their exact values. On the other hand, some constraints (such as demand fulfillment constraints and capacity constraints) are modeled linguistically as flexible constraints. Moreover, the final solution's robustness, particularly for the strategic decisions (i.e., those related to the network design such as facility location/allocation), is of great importance. Hence, in order to obtain a robust solution while handling various types of uncertainties, a robust mixed flexible-possibilistic programming (RMFPP) approach is tailored which substantially benefits from both FP and RO advantages. Later, the developed multi-objective model is solved using a well-known compromise solution approach, i.e., TH approach (Torabi and Hassini 2008). Finally, achieved results are analyzed considering different carbon emission policies (i.e., the carbon tax, cap, cap-and-trade, and offset mechanisms) in order to perform a comparative study between these policies to choose the best mechanism as well as investigating the impact of them on the considered OFs. Accordingly, we provide an illustrative example in the copier industry to show the practicability and usefulness of the developed optimization model.

The rest of the study is organized as follows. The relevant literature is comprehensively reviewed in Sect. 2. Problem definition, mathematical formulation, linearization of the nonlinear terms, and some extensions of the model under different carbon emission mechanisms are demonstrated in Sects. 3. The proposed RMFPP model and its crisp equivalent are elaborated in Sect. 4. The solution approach is provided in Sect. 5 which is then followed by an illustrative example, achieved results, and some sensitivity analyses on important parameters in Sect. 6. Lastly, Sect. 7 provides useful managerial implications of the proposed models and some avenues for further research.

2 Literature review

Here, the most relevant papers are reviewed in order to identify the research gaps and position our work in the literature. Benjaafar et al. (2013) considered various carbon mechanisms for procurement and production planning models. They presented a set of formulations that demonstrate how consideration of carbon emission can be used in operation management models. Palak et al. (2014) developed an economic lot-sizing model and presented four extensions of this model considering different carbon mechanisms to investigate the influence of these policies on decisions regarding the inventory replenishment in a biofuel SC. In another study, Waltho et al. (2019) comprehensively surveyed the approaches and models used in the design of a green SC focusing on selective mechanisms and approaches, which are used for pollution quantification. Their review showed the efficiency of four mechanisms including the cap, tax, cap-and-trade, and offset mechanisms in significantly reducing the environmental pollution with a slight increase in the total costs. They also investigated the main sources of emission and as it was expected, transportation accounted for one-third of the total emission. Establishing the facilities, disposing of, manufacturing, and storage are other sources of emission. Tanimizu and Amano (2016) presented a multi-objective integrated transportation and production scheduling to decrease CO_2 emission without reducing suppliers' profits. Coskun et al. (2016) framed a model for green SC network design based on consumer segmentation in which they considered three consumer segments and proposed a goal-programming model for it. Yavari and Geraeli (2019) formulated a multi-period, multi-product mixed-integer linear model to minimize environmental emission while minimizing total costs. They implemented robust optimization to hedge against uncertainty in demand, quality of the returned products, and products' return rate. Finally, they investigated the applicability of the developed model using a case study in the dairy industry. Tseng et al. (2019) conducted a comprehensive survey on challenges, trends, and opportunities in green SC management. The rest of the investigated research studies are summarized in Table 1.

The literature review reveals that although there are some research works addressing various carbon emission mechanisms in the (forward) SC problems, there is no similar study in the context of CLSCN design problem, while the optimal design of reverse SCs or CLSCs highly depends on the adopted carbon policies. Furthermore, coping with uncertain input data and soft constraints and robustness of the achieved solution have not been addressed jointly in the context of CLSCN design problem. To address these gaps, we formulate a novel mixed integer nonlinear programming (MINLP) model considering various carbon emission policies under uncertainty. In abstract, the main characteristics of this study which make it different from the existing works are summarized as below:

- Addressing a new multi-period, multi-product, three-objective CLSCN design problem which includes both long-term decisions (i.e., the locations, numbers, and capacities of MCs, WHs, DCs, and RCs) and mid-term decisions (i.e., the amounts of flows between different echelons of the CLSCN under study) in the forward and reverse directions, concurrently.

Table 1 Investigated research papers

	Type of SC	Product	Period	Sustainability measures	Type of uncertainty	Emission policy	Solution approach	Main decision variables
Wang et al. (2011)	F	M	S	C, G			E	ND
Fahimnia et al. (2013)	F, R	M	M	C		T	E	ND, TA, IL
Jin et al. (2014)	F	S	S	C		T, CA, CT	E	TA, BSC
Fareeduddin et al. (2015)	F, R	M	S	C		T, CA, CT	E	ND, TA, BSC
Fahimnia et al. (2015)	F	M	M	C		T	H	ND, TA, IL
Rezaee et al. (2015)	F	M	S	C	SP	CT	E	ND, TA, BSC
Tognetti et al. (2015)	F	M	S	C, G			E	ND, TA
Saffar et al. (2015)	F, R	M	M	C, G	PP		E, H	ND, TA
Ameknassi et al. (2016)	F	M	M	C, G	SP		E	ND, TA, IL
Talaei et al. (2016)	F, R	M	M	C, G	RO, PP		E	ND, TA
Tiwari et al. (2016)	F, R	M	M	P, G			H	TA, IL
Loni and Khamseh (2016)	F, R	M	S	C, G			E	ND, TA
Shaw et al. (2016)	F	S	S	C	SP	T, CA	E	ND, TA, BSC
Amalnick and Saffar (2017)	F, R	M	M	C, G	PP		E	ND, TA
Nurjanni et al. (2017)	F, R	S	S	C, G			E	ND, TA
Soleimani et al. (2017)	F, R	M	M	P, SO, CS	FLP	CA	H	ND, TA
Arampantzi and Minis (2017)	F	M	M	C, G, SO		CT	E	ND, TA, IL
Fazli-Khalaf et al. (2017)	F, R	S	S	C, G	RO, SP, PP		E	ND, TA
Safaei et al. (2017)	F, R	S	M	P	RO		E	ND, TA, IL
Zhen et al. (2018)	F, R	S	S	C	SP		H	ND, TA, IL
Sadeghi Rad and Nahavandi (2018)	F, R	M	M	C, G, CS			E	ND, TA, IL
Dehghan et al. (2018)	F, R	M	M	C	RP, SP, PP		E	ND, TA
Farrokh et al. (2018)	F, R	M	M	C	RO, SP, PP		E	ND, TA, IL
Fathollahi-Fard et al. (2018)	F, R	S	S	C, SO	SP		H	ND, TA

Table 1 (continued)

	Type of SC	Product	Period	Sustainability measures	Type of uncertainty	Emission policy	Solution approach	Main decision variables
Ma and Li (2018)	F, R	S	S	P	SP		E, H	ND, TA
Ghahremani-Nahr et al. (2019)	F, R	M	M	C	RO, PP		H	ND, TA, IL, SA
Mardan et al. (2019)	F, R	M	M	C, G			E	ND, TA, IL
Yavari and Geraeli (2019)	F, R	M	M	C, G	RO		H	ND, TA, IL
Zhen et al. (2019)	F, R	M	S	C, G	SP		E	ND, TA, IL
Our study	F, R	M	M	C, G	RO, PP, FLP	T, CA, CT, OF	E	ND, TA, IL, BSC

F forward, *R* reverse, *S* single, *M* multi, *C* cost, *G* greenhouse emission, *CS* customers satisfaction, *SO* social objective functions, *P* Profit, *RO* robust optimization, *PP* possibilistic programming, *FLP* flexible programming, *SP* stochastic programming, *T* tax mechanism, *CA* cap mechanism, *CT* cap-and-trade mechanism, *OF* offset mechanism, *E* exact, *H* heuristic/meta-heuristic, *ND* network design, *TA* transportation amount, *IL* inventory level, *SA* shortage amount, *BSC* buying/selling carbon credit

- Formulating a MINLP model (which is then linearized) considering different carbon emission policies (i.e., the carbon tax, cap, cap-and-trade, and offset policies).
- Developing an uncertain version of the original model using RMFPP approach in order to handle flexible constraints as well as coping with epistemic uncertainty in input parameters while achieving a final robust solution.

3 Problem definition

Increasing the awareness of consumers and their tendency towards purchasing and consuming eco/environment-friendly products, governmental legislation especially in connection with electronic equipment, along with the emergence of competitive markets urged decision-makers to pay more attention to environmental issues in the design of their SC networks. Besides, the structure of closed-loop SCs can result in waste reduction, decreasing disposal costs, etc. Therefore, green SC networks and closed-loop SC networks have attracted the attention of many researchers in recent years. Accordingly, in this research, a novel mixed-integer nonlinear programming model is presented to design a closed-loop green SC. The graphical demonstration of the concerned network is illustrated in Fig. 1, which includes multiple manufacturing centers (or MCs), warehouses (or WHs), customer zones, disassembling centers (or DCs), and remanufacturing centers (or RCs). Also, in order to transport products (new products, products to be disposed, and products to be remanufactured) from an echelon to a succeeding one, different types of transportations modes (i.e., road, rail, etc.) exist. In detail, new products (either new brand or remanufactured products) are dispatched from MCs/RCs to WHs and then from WHs to end-user zones to fully meet their forecasted demand. Thereafter, the returned units of products are accumulated in the DCs and after examination, those recoverable/recyclable products are transferred to RCs wherein the recycling process is performed. The optimal location and capacity of the SC's facilities (i.e., MCs, WHs, DCs, and RCs), the optimal quantity of produced/remanufactured, and disassembled products in the MCs/RCs, and DCs, respectively, and the optimal flow amount of products in the network in response to the forecasted

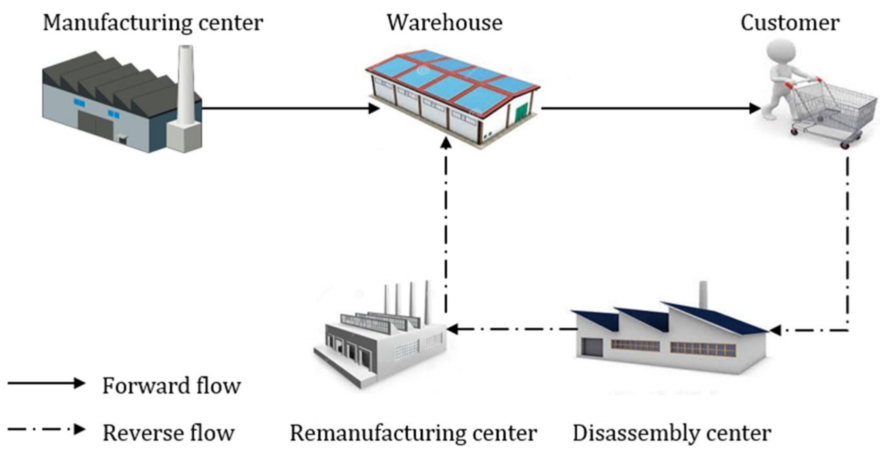


Fig. 1 Structure of the considered closed-loop supply chain network

demands over a multi-period long-term decision horizon are the main decisions which must be made in the developed optimization model.

The supplemental assumptions used for formulating the problem are as follows:

- All the customer demands must be fully met (i.e., no shortage is allowed), and a given percentage of the total demand is collected as returned products.
- To meet the demand of customers, intermodal transportation modes (e.g., road–rail, road–sea, etc.) are not allowed and all transportation modes have restricted capacity.
- The unit variable production cost depends on the quantity of products produced in the MCs, and therefore, the total production cost changes based upon a piecewise linear function.
- The unit variable remanufacturing cost depends on the number of remanufactured products, and therefore, the total remanufacturing cost changes based upon a piecewise linear function.

3.1 Mathematical formulation

The notations used to formulate the CLSCN design problem are presented in "Appendix". Using these notations, the MINLP model of the CLSCN design problem is as follows:

$$
\begin{aligned}
\min f_1 = {} & \underbrace{\sum_{f,n} f^1_{fn} x^1_{fn} + \sum_{w,n} f^2_{wn} x^2_{wn} + \sum_{i,n} f^3_{in} x^3_{in} + \sum_{j,n} f^4_{jn} x^4_{jn} - \sum_{f,n,j,n'} s_{fnjn'} x^1_{fn} x^4_{jn'}}_{\text{TFC}} \\
& + \underbrace{\sum_{p,f,t} v^1_{pft}(o_{pft}) o_{pft} + \sum_{p,w,t} v^2_{pwt} I_{pwt} + \sum_{p,c,i,l,t} v^3_{pct} w_{pcilt} + \sum_{p,c,i,l,t} v^4_{pit} w_{pcilt} + \sum_{p,j,t} v^5_{pjt}(\eta_{pjt}) \eta_{pjt}}_{\text{TVC}} \\
& + \underbrace{\sum_{p,f,w,l,t} t^1_{pfwlt} q_{pfwlt} + \sum_{p,w,c,l,t} t^2_{pwclt} u_{pwclt} + \sum_{p,c,i,l,t} t^3_{pcilt} w_{pcilt} + \sum_{p,i,j,l,t} t^4_{pijlt} y_{pijlt} + \sum_{p,j,w,l,t} t^5_{pjwlt} z_{pjwlt}}_{\text{TTC}}
\end{aligned}
\tag{1}
$$

The first OF (1) includes the total fixed costs (TFC) of opening facilities (i.e., establishment cost of MCs, WHs, DCs, and RCs minus the sum of saving costs of the established manufacturing and remanufacturing centers at the same candidate location), the total variable costs (TVC) including the costs of production, inventory holding, collecting, disassembling, and remanufacturing, and finally, the total transportation costs (TTC) in the network.

$$
\begin{aligned}
\min f_2 = {} & \underbrace{\sum_{p,f,t} e^1_{pf} o_{pft}}_{\text{EP}} + \underbrace{\sum_{p,w,t} e^{(2)}_{pw} I_{pwt}}_{\text{EH}} + \underbrace{\sum_{p,c,i,l,t} e^3_{pi} w_{pcilt}}_{\text{ED}} + \underbrace{\sum_{p,j,t} e^4_{pj} \eta_{pjt}}_{\text{ER}} \\
& + \underbrace{\sum_{p,l,t} e^{(5)}_{pl} \left(\sum_{f,w} r^1_{fw} q_{pfwlt} + \sum_{w,c} r^2_{wc} u_{pwclt} + \sum_{c,i} r^3_{ci} w_{pcilt} + \sum_{i,j} r^4_{ij} y_{pijlt} + \sum_{j,w} r^5_{jw} z_{pjwlt} \right)}_{\text{ET}}
\end{aligned}
\tag{2}
$$

The second OF (2) includes the total CO_2 emission [due to production activities (EP), inventory holding (EH), disassembling (ED), remanufacturing (ER), and transportation activities (ET)].

$$o_{pft} = \sum_{w,l} q_{pfwlt} \quad \forall p, f, t \tag{3a}$$

$$\eta_{pjt} = \sum_{w,l} z_{pjwlt} \quad \forall p, j, t \tag{3b}$$

Constraints (3a) and (3b) state that all the manufactured/remanufactured products should be shipped to warehouses and no inventory could be held at MCs/RCs, respectively.

$$\eta_{pjt} = \sum_{i,l} y_{pijlt} \quad \forall p, j, t \tag{4}$$

Constraint (4) expresses that each shipped product from DCs to a given RC via any transportation mode in each period must be remanufactured successfully.

$$\sum_{p} o_{pft} \le \sum_{n} h^1_{fn} x^1_{fn} \quad \forall f, t \tag{5a}$$

$$\sum_{p,f,l} q_{pfwlt} + \sum_{p,j,l} z_{pjwlt} + \sum_{p} I_{pw,t-1} \le \sum_{n} h^2_{wn} x^2_{wn} \quad \forall w, t \tag{5b}$$

$$\sum_{p,c,l} w_{pcilt} \le \sum_{n} h^3_{in} x^3_{in} \quad \forall i, t \tag{5c}$$

$$\sum_{p,i,l} y_{pijlt} \le \sum_{n} h^4_{jn} x^4_{jn} \quad \forall j, t \tag{5d}$$

Constraints (5a)–(5d) address capacity constraints of the MCs, WHs, DCs, and RCs, respectively. Constraint (5a) states that in a given period, the total amount of manufactured goods in a given MC cannot surpass its corresponding production capacity. Constraint (5b) states that in a given period, the total number of shipped products from all MCs/RCs to a given WH through any transportation option plus remained inventory in this WH at the end of the previous period must be exactly the same as or less than the capacity of the respective WH. Constraint (5c) expresses that the total number of collected products from all customers which are sent to a given DC via any transportation option must be equal or less than the capacity of the corresponding DC in each period. Constraint (5d) represents that in a given period, the total number of products sent to a given RC from all DCs and through any transportation option must be equal or less than the capacity of the respective RC.

$$\sum_{n} x^1_{fn} \le 1 \quad \forall f \tag{6a}$$

$$\sum_{n} x^2_{wn} \le 1 \quad \forall w \tag{6b}$$

$$\sum_{n} x^3_{in} \le 1 \quad \forall i \tag{6c}$$

$$\sum_{n} x_{jn}^{4} \leq 1 \quad \forall j \tag{6d}$$

Constraints (6a–6d) guarantee that each facility (i.e., MC, WH, DC, RC) is established at most in one of its capacity levels.

$$\sum_{f,l} q_{pfwlt} + \sum_{j,l} z_{pjwlt} + I_{pw,t-1} - I_{pwt} = \sum_{c,l} u_{pwclt} \quad \forall p, w, t \tag{7}$$

Constraint (7) is the flow balance constraint for each product in each period and in each warehouse.

$$\sum_{w,l} u_{pwclt} \geq d_{cpt} \quad \forall c, p, t \tag{8}$$

Constraint (8) guarantees that in each period, demand of each customer for each product must be completely met.

$$\sum_{i,l} w_{pcilt} \geq \alpha_p . d_{cpt} \quad \forall c, p, t \tag{9a}$$

$$\sum_{j,l} y_{pijlt} \geq \alpha'_p \sum_{c,l} w_{pcilt} \quad \forall i, p, t \tag{9b}$$

Constraints (9a) and (9b) are the reverse flow constraints. Constraint (9a) guarantees that in a given period, all the returned products (of each type) from each customer should be collected. Also, Constraint (9b) states that in a given period, all the recoverable/recyclable products of each type (as a percentage of brought back goods) must be sent from DCs to RC via any transportation option.

$$o_{pft},\ q_{pfwlt},\ u_{pwclt},\ I_{pwt},\ w_{pcilt},\ y_{pijlt},\ \eta_{pjt},\ z_{pjwlt} \geq 0 \quad \forall p,\ f,\ w,\ c,\ i,\ j,\ t \tag{10a}$$

$$x_{fn}^{1},\ x_{wn}^{2},\ x_{in}^{3},\ x_{jn}^{4} \in \{0, 1\} \quad \forall f,\ w,\ i,\ j,\ n,\ n' \tag{10b}$$

Constraints (10a) and (10b) show the types of decision variables.

3.2 Linearization of the nonlinear terms

As achieving the global solutions of nonlinear models are computationally troublesome or unattainable in most cases (Babazadeh et al. 2017), different linearization techniques have been developed in the literature. In the proposed model, some of the sentences in the OF (1) are nonlinear which need to be linearized.

Multiplication of two binary variables (i.e., $x_{fn}^{1} \times x_{jn'}^{4}$) in the last term of TFC leads to the nonlinearity of the OF. However, according to Glover and Woolsey (1974), by defining a new variable $\bar{x}_{fnjn'}$ and two sets of additional constraints, the linear equivalent of TFC can be formulated as below:

$$\text{TFC} = \sum_{f,n} f_{fn}^{1} x_{fn}^{1} + \sum_{w,n} f_{wn}^{2} x_{wn}^{2} + \sum_{i,n} f_{in}^{3} x_{in}^{3} + \sum_{j,n} f_{jn}^{4} x_{jn}^{4} - \sum_{f,j,n,n'} s_{fnjn'} \bar{x}_{fnjn'} \tag{11}$$

s.t.

$$x_{fn}^{1}+x_{jn'}^{4}\geq 2\bar{x}_{fnjn'}\quad \forall f,j,n,n' \tag{12}$$

$$\bar{x}_{fnjn'}\geq x_{fn}^{1}+x_{jn'}^{4}-1\quad \forall f,j,n,n' \tag{13}$$

$$\bar{x}_{fnjn'}\in\{0,1\}\quad \forall f,j,n,n' \tag{14}$$

In many enterprises, increasing the quantity of production/remanufacturing leads to decrease in the unit variable production/remanufacturing cost owing to economies of scale principle (Mirzapour Al-e-hashem et al. 2013). Accordingly, in the first and the last terms of TVC, the variable production and remanufacturing costs (i.e., $v_{pft}^{1}(o_{pft})o_{pft}$ and $v_{pjt}^{5}(\eta_{pjt})\eta_{pjt}$) depend on the number of produced/remanufactured products in the manufacturing/remanufacturing centers, respectively. As Fig. 2 shows, these values should be found via a piecewise function, which is another type of nonlinearity in the proposed model.

The above-mentioned nonlinear function can be represented as follows:

$$v_{pft}^{1}(o_{pft})o_{pft}=\begin{cases} v_{1}^{1}+\lambda_{1}(o_{pft}-o_{1}) & \text{if}\quad o_{1}\leq o_{pft}\leq o_{2}\\ v_{2}^{1}+\lambda_{2}(o_{pft}-o_{2}) & \text{if}\quad o_{2}\leq o_{pft}\leq o_{3}\\ v_{3}^{1}+\lambda_{3}(o_{pft}-o_{3}) & \text{if}\quad o_{3}\leq o_{pft}\leq o_{4}\\ \cdot & \\ \cdot & \\ \cdot & \\ v_{m-1}^{1}+\lambda_{(m-1)}(o_{pft}-o_{m-1}) & \text{if}\quad o_{m-1}\leq o_{pft}\leq o_{m} \end{cases} \tag{15}$$

where λ_i is the slope when the amount of production is between o_i and o_{i+1}, and m represents that there are $(m-1)$ line segments in the piecewise linear function of production cost. This formulation could be linearized using the appropriate linearization technique presented by Mirzapour Al-e-hashem et al. (2013). Via this method, the variable o_{pft} is converted to $m-1$ independent variables, i.e., $o_{pft}^{(m)}$, where; $o_{pft}=\sum_{m'=1}^{m-1}o_{pft}^{(m')}$.Thus, the manufacturing cost in the first OF can be expanded as follows:

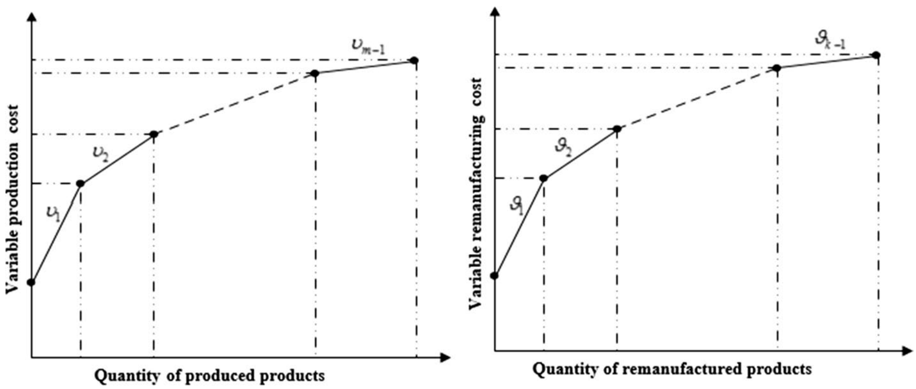


Fig. 2 Piecewise functions of production/remanufacturing costs

$$v^{1}_{pft}(o_{pft})o_{pft} = \begin{cases} v^{1}_{pft_1} + \lambda_{pft_1}(o^{(1)}_{pft} - \mathrm{o}_1) \mathit{if}\ \mathrm{o}_1 \le o^{(1)}_{pft} \le o_2 \\ v^{1}_{pft_2} + \lambda_{pft_2}(o^{(2)}_{pft} - \mathrm{o}_2) \mathit{if}\ \mathrm{o}_2 \le o^{(2)}_{pft} \le o_3 \\ v^{1}_{pft_3} + \lambda_{pft_3}(o^{(3)}_{pft} - \mathrm{o}_3)\ \mathit{if}\ \mathrm{o}_3 \le o^{(3)}_{pft} \le o_4 \\ . \\ . \\ . \\ v^{1}_{pft_{(m-1)}} + \lambda_{pft_{(m-1)}}(o^{(m-1)}_{pft} - \mathrm{o}_{m-1})\ \mathit{if}\ \mathrm{o}_{m-1} \le o^{(m-1)}_{pft} \le o_m \end{cases} \tag{16}$$

Now, by defining a new binary variable (s) and with the help of $m-1$ constraints, the linear counterpart of the piecewise function (16) would be rewritten as:

$$v^{1}_{pft}(o_{pft})o_{pft} = \sum_{m'=1}^{m-1} v^{1}_{pft_{(m')}} s_{pft_{(m')}} + \lambda_{pft_{(m')}} \left(o^{(m')}_{pft} - o_{pft_{(m')}} \right) \quad \forall p, f, t \tag{17}$$

$$o_{pft_{(m-1)}} s_{pft_{(m-1)}} \le o^{(m-1)}_{pft} \le o_{pft_{(m)}} s_{pft_{(m-1)}} \quad \forall p, f, t, m \tag{18}$$

$$o_{pft} = \sum_{m'=1}^{m-1} o^{(m')}_{pft} \quad \forall p, f, t \tag{19}$$

$$\sum_{m'=1}^{m-1} s_{pft_{(m')}} = 1 \quad \forall p, f, t \tag{20}$$

$$s_{pft_{(m)}} \in \{0, 1\} \quad \forall p, f, t, m \tag{21}$$

$$o^{(m)}_{pft} \ge 0 \quad \forall p, f, t, m \tag{22}$$

Using a similar method, the variable remanufacturing cost can also be transformed to its linear counterpart.

3.3 Model extension by considering different carbon mechanisms

In this section, the original model is extended using different carbon mechanisms. These mechanisms include the carbon tax, cap, cap-and-trade, and offset mechanisms. Notably, these limitations are determined by policy makers or governmental regulations and may vary depending on company in which they operate. The definition and formulation of each policy are stated as follow:

3.3.1 Carbon tax mechanism

In this mechanism, a penalty cost is incurred for each unit of CO_2 emission in the production and remanufacturing operations (Palak et al. 2014). Let δ indicates the carbon tax rate per unit of CO_2 emitted. Accordingly, this mechanism can be modeled as below:

$$\min f_1' = f_1 + \delta(\text{EP} + \text{ER}) \tag{23}$$

3.3.2 Carbon cap mechanism

Under this mechanism, the sum of carbon released due to the manufacturing and remanufacturing processes cannot exceed this cap. This limitation can be simply addressed in the proposed model through adding Eq. (24) (Palak et al. 2014).

$$\text{EP} + \text{ER} \leq C^{\text{cap}} \tag{24}$$

3.3.3 Carbon cap-and-trade mechanism

In this mechanism, it is assumed that there is a carbon market in which each company is allowed to sell unused carbon credits to other firms or buy required carbon credits to meet its end-user demand (Palak et al. 2014). Let δ^+ and δ^-, p^+, and p^- denote the carbon credits purchased, carbon credits sold, carbon buying price, and carbon selling price in the carbon market, respectively. Notably, the carbon buying and selling prices are determined in the carbon trading markets and their values can vary depending on the market's prices, company, and the market in which it operates. Thus, this mechanism can be framed as below:

$$\min f_1'' = f_1 + \sum_t \left(p^+\delta_t^+ - p^-\delta_t^-\right) \tag{25}$$

$$\text{EP} + \text{ER} + \sum_t \delta_t^- \leq C^{\text{cap}} + \sum_t \delta_t^+ \tag{26}$$

3.3.4 Carbon offset mechanism

This mechanism is analogous to the previous mechanism, except that the firm cannot sell its unused carbon credits. In the other words, under this mechanism, the firm is only allowed to purchase carbon credits and there is no benefit if the emission is less than its nominal cap (Palak et al. 2014). Let δ^+ and p^0 denote the purchased carbon credits and carbon offset price per kg in the carbon market, respectively. Hence, the mathematical formulation of this mechanism will be as below:

$$\min f_1''' = f_1 + \sum_t p^0\delta_t^+ \tag{27}$$

$$\text{EP} + \text{ER} \leq C^{\text{cap}} + \sum_t \delta_t^+ \tag{28}$$

4 Robust mixed flexible-possibilistic programming (RMFPP) approach

Due to the simultaneous existence of different types of uncertainty in the supply chain planning problems, in recent years, the combination of different uncertainty programming approaches are progressively used to hedge against various types of uncertainty. Since the framework of the concerned problem in this article is similar to that of Pishvaee and Fazli Khalaf (2016), the same version of RMFPP approach is applied here which is well summarized in Fig. 3.

Also, the well-known triangular possibility distribution is used in this study, because of its practicality and simplicity to formulate the imprecise coefficients that could be defined by three prominent points, e.g., $\varsigma = (\varsigma^{p}, \varsigma^{m}, \varsigma^{o})$. It is assumed that both capacity and demand constraints are flexible constraints by which a deviation from their targets is allowed to some extent. In addition to the aforementioned flexible constraints, it is also assumed that the opening costs, saving costs, transportation costs, capacity of facilities, and demands of customers are tainted with epistemic uncertainty and therefore are shown by triangular possibility distributions.

Accordingly, the RMFPP version of the original model (1)–(22) is stated as follows:

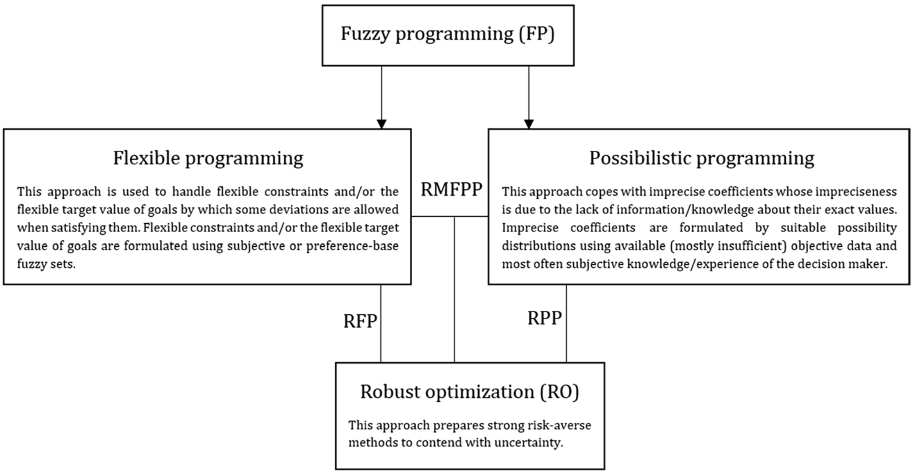


Fig. 3 Uncertainty programming approaches

$$
\begin{aligned}
&\text{Min } z_1 = \overbrace{\left(\frac{f^1+f^2+f^3}{3}\right)}^{\text{Expected value}} x + \overbrace{\left(\frac{c^1+c^2+c^3}{3}\right)}^{\text{Expected value}} y; \quad \text{Min } z_2 = ey;\\
&\text{Min } z_3 = \underbrace{\pi_1}_{\text{Imprtance weight}} \left[\underbrace{\left[f^o x + c^o y\right] - \left[\left(\frac{f^1+f^2+f^3}{3}\right)x + \left(\frac{c^1+c^2+c^3}{3}\right)y\right]}_{\text{Maximum deviation over the expected value of } z_1} \right]\\
&\quad + \underbrace{\pi_2}_{\text{Unit penalty cost}} \underbrace{\left[\rho\left(\frac{N^p+N^m}{2}\right) + (1-\rho)\left(\frac{N^m+N^o}{2}\right) - N^p\right]x}_{\text{Gap between selected value of uncertain parameters and worst case value}}\\
&\quad + \underbrace{\pi_3}_{\text{Unit penalty cost}} \underbrace{\left[d^o - \sigma\left(\frac{d^m+d^o}{2}\right) - (1-\sigma)\left(\frac{d^p+d^m}{2}\right)\right]}_{\text{Gap between selected value of uncertain parameters and worst case value}}\\
&\quad + \underbrace{\pi_4}_{\text{Unit penalty cost}} \underbrace{\left[\left(t^m + \frac{\phi_t - \phi'_t}{3}\right)(1-\chi)\right]x}_{\text{Soft constraint's possible violation}} + \underbrace{\pi_5}_{\text{Unit penalty cost}} \underbrace{\left[\left(r^m + \frac{\varphi_r - \varphi'_r}{3}\right)(1-\beta)\right]}_{\text{Soft constraint's possible violation}}\\
&\text{s.t:} \quad Ay \le \left[\rho\left(\frac{N^p+N^m}{2}\right) + (1-\rho)\left(\frac{N^m+N^o}{2}\right)\right]x + \left[\left(t^m + \frac{\phi_t - \phi'_t}{3}\right)(1-\chi)\right]x;\\
&\quad Bx \le 1; \quad Lx = 0;\\
&\quad Sy \ge \left[\sigma\left(\frac{d^m+d^o}{2}\right) + (1-\sigma)\left(\frac{d^p+d^m}{2}\right)\right] - \left(r^m + \frac{\varphi_r - \varphi'_r}{3}\right)(1-\beta);\\
&\quad x \in \{0,1\}, y \ge 0,\ 0 \le \chi, \beta \le 1,\ 0.5 < \rho, \sigma \le 1.
\end{aligned}
\tag{29}
$$

It should be noted that in all the previous studies, which have applied the robust fuzzy programming approach (see, e.g., Pishvaee et al. 2012; Pishvaee and Fazli Khalaf 2016), the robustness cost is added as a virtual penalty to the economic OF which typically includes real costs such as fixed costs, transportation costs. However, as robustness costs are not a real part of operating costs, logically they cannot be summed in a single objective in line with the other operating costs. Nevertheless, if these virtual costs are to be integrated by the real costs, when the model is solved using a multi-objective approach such as TH approach, the decision-maker (DM) would not be able to distinguish the shares of real and virtual costs. Indeed, under this undesirable integration, it is possible that a given solution outperforms another solution while its real operating cost is more than this solution which could be misleading. Therefore, in this paper, a separate OF (i.e., the robustness cost) is utilized to deal with the above-mentioned deficiencies.

As the second and fourth terms in the third OF (z_3), as well as the first constraint, are non-linear sentences (in the form of multiplication of a binary and a positive variable), by defining two auxiliary variables and six sets of additional constraints (Pishvaee et al. 2012), the linear counterpart of the model (29) is reformulated as follows:

$$
\begin{aligned}
&\text{Min } z_1 = \left(\frac{f^1 + f^2 + f^3}{3}\right)x + \left(\frac{c^1 + c^2 + c^3}{3}\right)y; \quad \text{Min } z_2 = ey; \\
&\text{Min } z_3' = \pi_1\left[\left[f^o x + c^o y\right] - \left[\left(\frac{f^1 + f^2 + f^3}{3}\right)x + \left(\frac{c^1 + c^2 + c^3}{3}\right)y\right]\right] \\
&\qquad + \pi_2\left[\mu\left(\frac{N^p + N^m}{2}\right) + (x - \mu)\left(\frac{N^m + N^o}{2}\right) - N^p\right] \\
&\qquad + \pi_3\left[d^o - \sigma\left(\frac{d^m + d^o}{2}\right) - (1 - \sigma)\left(\frac{d^p + d^m}{2}\right)\right] \\
&\qquad + \pi_4\left[\left(t^m + \frac{\phi_t - \phi_t'}{3}\right)(x - \varepsilon)\right] + \pi_5\left[\left(r^m + \frac{\varphi_r - \varphi_r'}{3}\right)(1 - \beta)\right] \\
&\text{s.t:} \quad Ay \le \left[\rho\left(\frac{N^p + N^m}{2}\right) + (1 - \rho)\left(\frac{N^m + N^o}{2}\right)\right]x + \left[\left(t^m + \frac{\phi_t - \phi_t'}{3}\right)(1 - \chi)\right]x; \\
&\qquad Bx \le 1; \quad Lx = 0; \\
&\qquad Sy \ge \left[\sigma\left(\frac{d^m + d^o}{2}\right) + (1 - \sigma)\left(\frac{d^p + d^m}{2}\right)\right] - \left(r^m + \frac{\varphi_r - \varphi_r'}{3}\right)(1 - \beta); \\
&\qquad \mu \le Mx; \quad \mu \ge M(x - 1) + \rho; \quad \mu \le \rho; \quad \varepsilon \le Mx; \quad \varepsilon \ge M(x - 1) + \chi; \quad \varepsilon \le \chi; \\
&\qquad x \in \{0, 1\}; y, \ \mu, \ \rho \ge 0; 0 \le \chi, \beta \le 1; 0.5 < \rho, \sigma \le 1.
\end{aligned}
\tag{30}
$$

5 Solution approach

In the literature, there are various methods to deal with multi-objective programs (MOP), among them fuzzy programming methods, due to their capability in measuring the satisfaction degrees of OFs directly, are extensively used. In this paper, a powerful FP method proposed by Torabi and Hassini (2008) named as TH approach is used to solve the proposed multi-objective model. Unlike the other classical multi-objective methods (e.g., the weighted-sum, conventional ε-constraint, and goal programming) that may lead to the weakly efficient solutions, the TH approach just generates efficient (i.e., Pareto-optimal) solutions by setting different values for the coefficient of compensation and objectives' weights (Zahiri and Pishvaee 2016). The TH method is summarized in Fig. 4.

6 Implementation and evaluation

Among the different industries and sectors, waste of the electronic and electrical equipment has been identified as the third biggest origin of environmental pollution (transportation and food consumption are on the top of the list). Accordingly, this sector has been widely investigated by several scholars, among them, the copier (re)manufacturing industry (see, e.g. Fleischmann et al. 2009; Talaei et al. 2016; Ayres et al. 1997; Thierry et al. 1995) is the most-explored application area. Since the structure of the concerned network in this study is rather similar to the recently published research by Talaei et al. (2016), to validate the practicability and efficiency of the presented optimization-based mathematical model, inspiring by the benchmarked case study in that research, a tailored case study is provided which suitably fits to the context of this research.

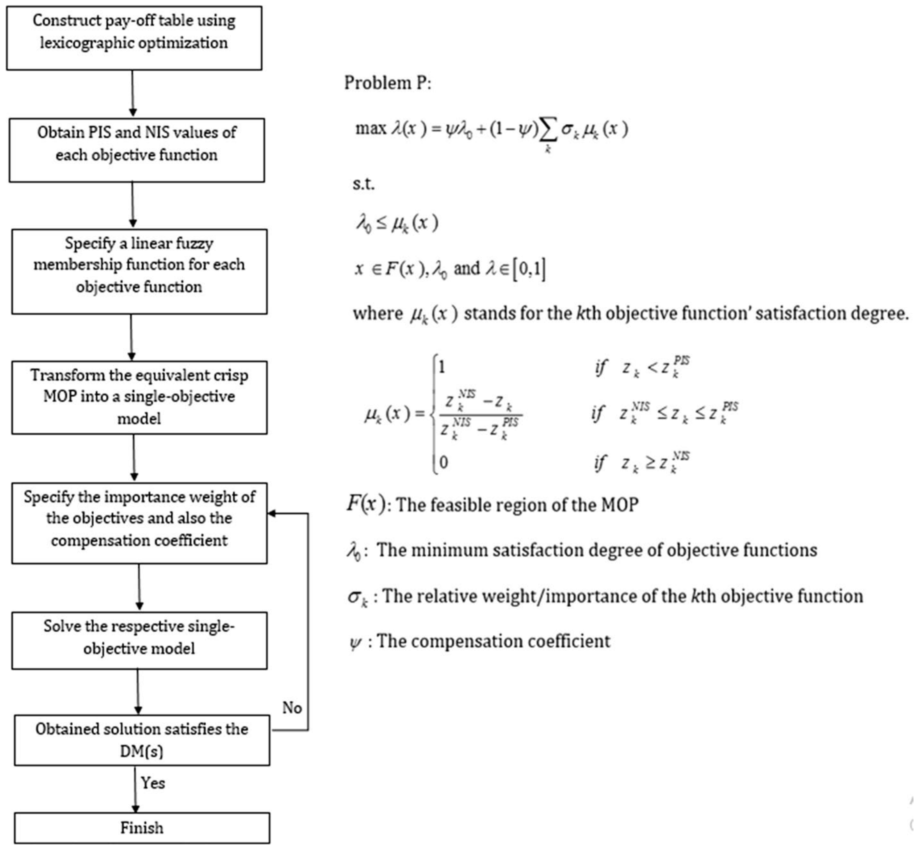


Fig. 4 Structure of the solution approach

The gathered data are related to the electronics industry, namely Alfa firm which produces and distributes some products (in the forward direction), and in the reverse direction, collects and remanufactures the used products. In this case, four potential locations are considered for establishing manufacturing centers by which final goods are produced and delivered to customer zones through some warehouses. Four potential locations are also considered for establishing required warehouses. There are five customer zones with known and fixed locations. The returned products are collected via three DCs that their number and locations must be determined through solving the proposed model. A predetermined percentage of disassembled products would be transported to remanufacturing centers for which there are three candidate locations. It is assumed that there are three capacity levels for opening each facility (i.e., MCs, warehouses, DCs, and RCs) and two families of products, two transportation modes, and two (e.g., semi-annual) planning periods. Furthermore, specific uniform distributions (see Table 2) have been utilized to randomly generate the values of the second OF's parameters. It is worth

Table 2 Size of the numerical illustration

$\lvert P\rvert = 2$	$\lvert C\rvert = 5$	$\lvert I\rvert = 3$	$\lvert W\rvert = 4$
$\lvert L\rvert = 2$	$\lvert T\rvert = 2$	$\lvert F\rvert = 4$	$\lvert J\rvert = 3$

Table 3 The uniform distributions utilized to generate the input data

$f_{fn}^1 \approx U(350, 650) * 10^3$	$f_{wn}^2 \approx U(200, 250) * 10^3$	$f_{in}^3 \approx U(100, 150) * 10^3$	$f_{jn}^4 \approx U(200, 250) * 10^3$
$t_{pfwlt}^1, t_{pwclt}^2, t_{pcilt}^3, t_{pijlt}^4, t_{pjwlt}^5 \approx U(4, 10)$		$h_{fn}^1 \approx U(500, 800)$	$h_{wn}^2 \approx U(200, 300)$
$h_{in}^3 \approx U(200, 350)$	$h_{jn}^4 \approx U(250, 350)$	$d_{cpt} \approx U(60, 140)$	$e_{pf}^1 \approx U(5, 10)$
$e_{pw}^2 \approx U(2, 4)$	$e_{pi}^3 \approx U(4, 6)$	$e_{pj}^4 \approx U(5, 8)$	$e_{pl}^5 \approx U(4, 5)$

Table 4 Constructed pay-off table

	z_1^*	z_2^*	$z_3'^*$
z_1 (minimization)	2.293460E+7	528,635.988	4,784,724.020
z_2 (minimization)	2.982770E+7	517,079.377	4,201,773.879
z_3' (minimization)	3.043829E+7	637,615.923	3,969,475.057

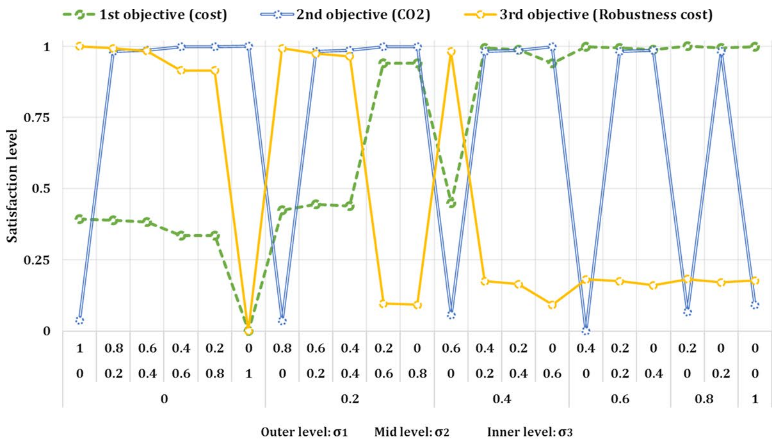
noting that for each imprecise parameter, the most likely value (i.e., ς^m) of the related possibility distribution is first generated using the proposed ranges in Table 3, and the other prominent points are then obtained by considering 10% perturbation over and under the most likely value, leading to the possibility distribution $(0.9 * \varsigma^m, \varsigma^m, 1.1 * \varsigma^m)$. All the experiments are performed using GAMS 24.8.2 software on a Laptop with Core i7 2.2 GHz CPU and 6 GB RAM.

6.1 Results and discussions

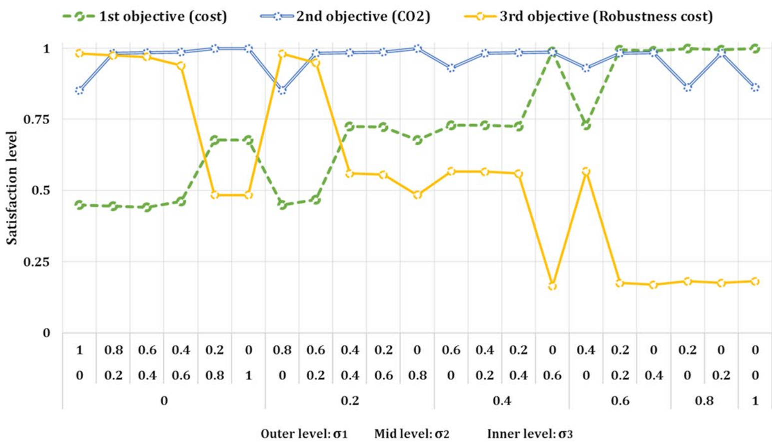
In this part, the proposed three-objective model is solved and then some numerical analyses are carried out. To this end, the pay-off table is first constructed using the lexicographic method (see Mavrotas 2009 for the details of the pay-off table construction process). Table 4 shows the constructed pay-off table.

As mentioned before, σ and Ψ are two important parameters of the TH approach. The former addresses the OFs' relative importance vector while the latter makes a balance between the weighted sum of OFs' satisfaction levels and their minimum satisfaction level. Obviously, any adjustment in the values of σ and Ψ will influence the obtained Pareto-optimal solution. As a preliminary test of the influence of different carbon emission mechanisms on the optimal structure of the network, the values of these parameters must be set. Hence, in order to obtain the most preferred values of these parameters, a comprehensive sensitivity analysis is executed whose results are demonstrated in Fig. 5a–e. For the sake of simplicity in presentation, the corresponding values of OFs in the achieved solutions are normalized and are then reported in the figures. Indeed, in an achieved solution, if an OF gets its best value (PIS), then its normalized value (i.e., the satisfaction degree) will be 1 and if its value approaches to its corresponding NIS value, its normalized value approaches 0.

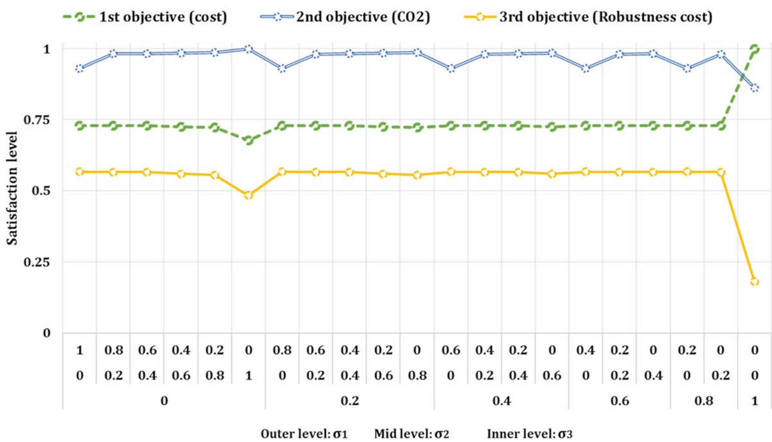
As can be seen in Fig. 5a–e, whenever the values of Ψ are small, TH approach aims at maximizing the aggregated OFs' satisfaction level while when the values of Ψ are high, this approach aims to maximize the minimum satisfaction level of OFs. These figures also demonstrate that in each interval and under given values of σ_1 and Ψ, when the relative importance of the second OF (σ_2) increases, its satisfaction degree increases (μ_2) while the third OF's satisfaction degree decreases (μ_3) showing their confliction in practice. Also,



(a) Results of analyzing TH's parameters (Ψ=0)

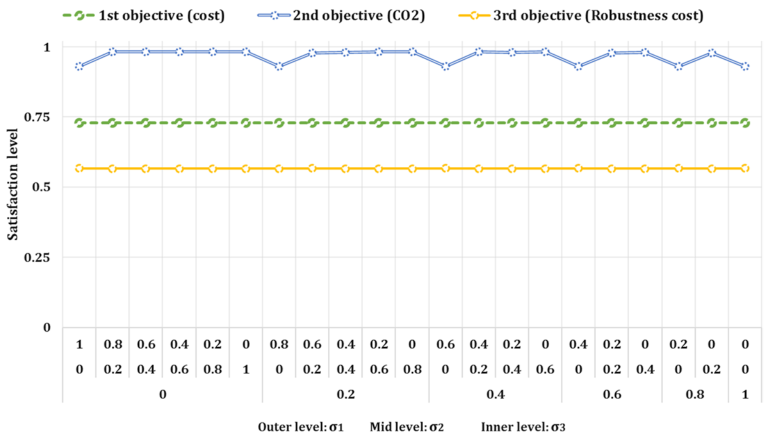


(b) Results of analyzing TH's parameters (Ψ=0.25)

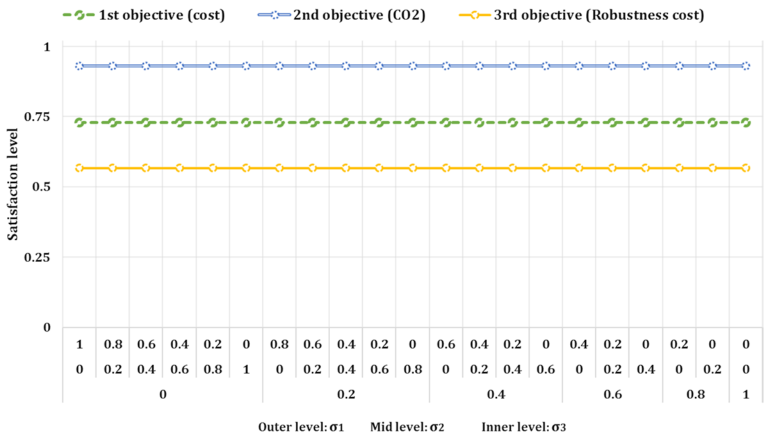


(c) Results of analyzing TH's parameters (Ψ=0.5)

Fig. 5 Results of analyzing TH's parameters **a** ($\Psi=0$), **b** ($\Psi=0.25$), **c** ($\Psi=0.5$), **d** ($\Psi=0.75$), **e** ($\Psi=1.0$)



(d) Results of analyzing TH's parameters (Ψ=0.75)



(e) Results of analyzing TH's parameters (Ψ=1.0)

Fig. 5 (continued)

it can be concluded from the figures that higher values of the parameter Ψ (i.e., the coefficient of compensation) cause less fluctuation in the OFs' satisfaction degrees as it puts more pressure on escalating the minimum satisfaction degree of OFs. As an extreme case, when the value of Ψ equals 1, any changes in the value of OFs' relative weights do not affect the achieved compromised solution while in the opposite extreme case ($\Psi = 0$), a considerable effect on the achieved solution is observed when a minor change occurs in these coefficients.

As could be seen, among different settings for the values of TH parameters, all the objectives get suitable satisfaction levels when the value of parameters σ_1, σ_2, σ_3, and Ψ are defined as 0.4, 0.4, 0.2, and 0.25, respectively. In this setting, the first, second, and third OFs get the values 2.6629E+07, 5.2880E+05, and 4.3709E+06 which could be translated as 72.5%, 98.4%, and 56.0% satisfaction levels, respectively. As Fig. 5a–e shows, the satisfaction level of the last OF (i.e., the robustness cost) exceeds 95% only in those settings where the relative weights of other objectives (i.e., the first and second objectives) equal 0 or rather small number. Nevertheless, in other settings (when the two other objectives have positive but not such small values), the third OF's satisfaction level would not exceed 57%. As a result, in the suggested setting, the first two objectives perform well while the last objective performs reasonably. Therefore, for the rest of the numerical analyses, the suggested setting is adopted.

Hereafter, the effects of applying various carbon emission mechanisms in the achieved compromised solutions are analyzed and compared. To do so, first, the minimum carbon emission required for production and remanufacturing activities is computed through minimizing the second OF. The results show that the manufacturing and remanufacturing activities require at least 17,950 carbon credits in order to maintain the supply chain activities and efficiently meet the customer's demand. Then, according to the literature, the values of carbon cap allowance, carbon tax, carbon buying/selling prices, and carbon offset price are fixed as 18,000, 30, 10, 10, and 10, respectively. The achieved results under each mechanism are demonstrated in Table 5.

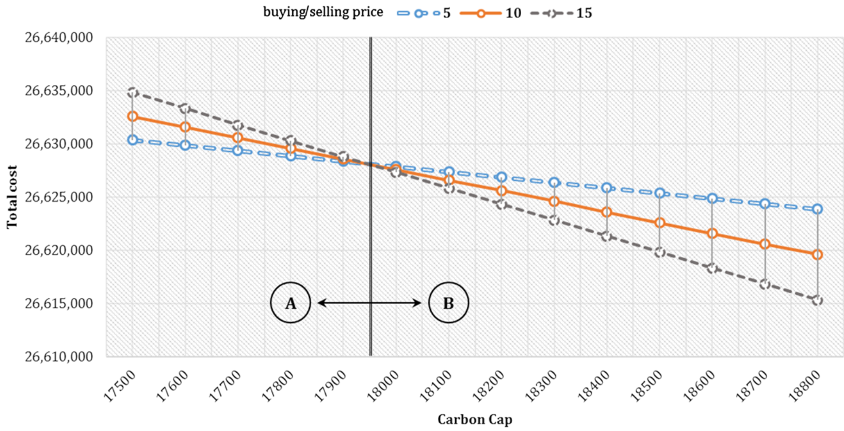
As Table 5 indicates, the cap-and-trade mechanism has the least total cost and the best robustness cost while the tax mechanism has the least total CO_2 emission. Accordingly, since each mechanism could outperform in one or more objectives, the preference of DM would determine the best carbon emission policy. If the priority of DM is minimizing the first or third OF, the cap-and-trade mechanism will be the most preferred mechanism. However, if the DM aims at minimizing the second OF, the carbon tax policy would be suggested.

As it was discussed earlier, the cap-and-trade mechanism is among the most efficient mechanisms which is also highly flexible policy compared to the other policies. This policy permits the firm to sell its unused carbon credits, when the size of carbon cap is large, to make additional income or conversely buy carbon credits if required in order to meet the end-users demand. As a result, this mechanism could be suggested in the problems similar to the framework of the concerned problem in this article. The obtained results of sensitivity analysis performed on this policy are demonstrated in Fig. 6a–c.

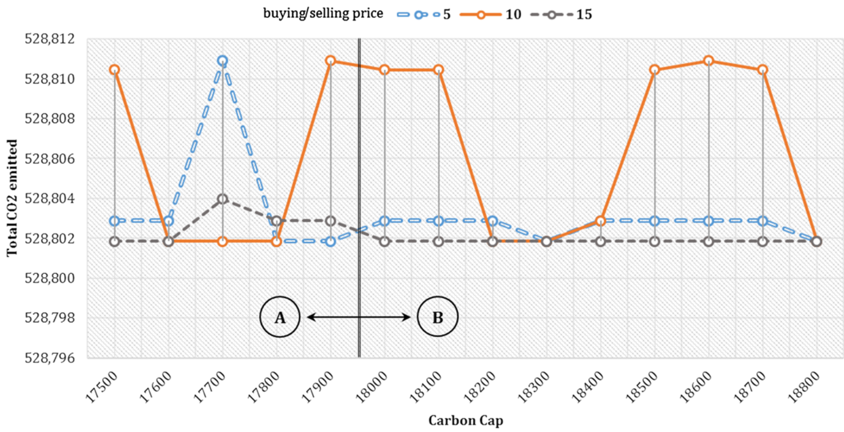
As Fig. 6a illustrates, using the cap-and-trade mechanism, the company exactly needs 17,950 carbon cap allowance. In this point (the boundary line), if the buying/selling price increases/decreases, as it is neither needed to buy an extra carbon credit nor an extra carbon credit remains to be sold, no changes in the total costs occur. However, when the carbon credit is strictly less than 17,950 units (area A where an extra amount of carbon credit should be bought to meet the customer's demands), if the buying/selling price increases, one should pay more to buy extra credit, which results an increase in the total costs. In contrast, whenever the carbon credit is strictly more than 17,950 units (area B where an extra amount of carbon credits remains and can be sold in the market), if the buying/selling price increases, one could earn more money on selling its extra credit, which leads to decrease in the total costs. Also Fig. 6a represents that under the same value of carbon buying and

Table 5 Comparative results of different carbon emission mechanisms ($\delta = 30$, $\rho^{+} = \rho^{-} = \rho^{0} = 10$, Cap = 18,000)

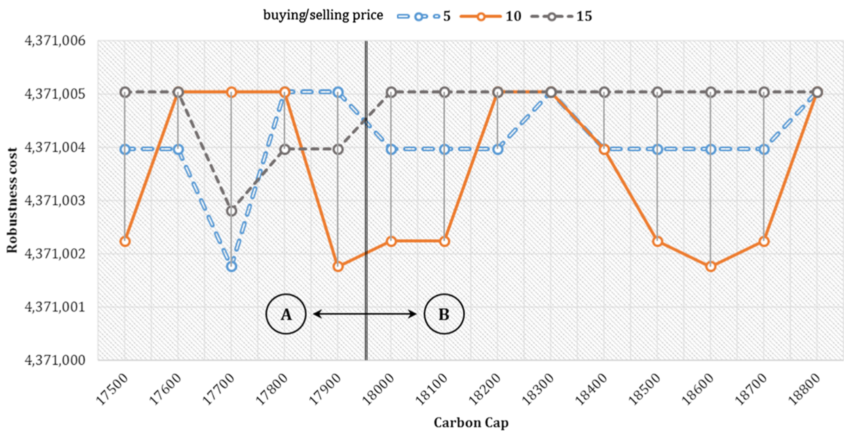
Carbon policy	First objective (total cost)	Second objective (total CO_2 emission)	Third objective (robustness cost)
Carbon cap	2.662928E+7	528,814.395	4,370,888.241
Carbon tax	2.688726E+7	528,803.975	4,398,917.186
Carbon cap-and-trade	2.662900E+7	528,810.455	4,370,858.873
Carbon offset	2.662928E+7	528,814.395	4,370,888.241



(a) Results of analyzing the cap-and-trade mechanism (1st objective)



(b) Results of analyzing the cap-and-trade mechanism (2nd objective)



(c) Results of analyzing the cap-and-trade mechanism (3rd objective)

Fig. 6 Results of analyzing the cap-and-trade mechanism **a** (first objective), **b** (second objective), **c** Results of analyzing the cap-and-trade mechanism (third objective) selling prices, when the cap allowance increases, as the firm needs to buy less carbon credits or sell more unused carbon credits, the total cost decreases. In contrast, when the carbon cap size decreases, as the firm needs to buy additional carbon credits to meet the customers' demand or sell less unused carbon (if extra amount exists), the total cost increases. Nevertheless, such a clear trend could not be identified in Figs. 6b, c. Please note that the changes in the value of second and third OFs are quite negligible as their values ranges in (528,802, 528,811) and (4,371,001.8, 4,371,005), respectively.

It is noteworthy that the complexity of the developed optimization-based mathematical model depends on the number of binary/positive/bounded variables as well as the number of constraints, which are demonstrated in Table 6. It should be noted that the size of sets related to indices f, w, i, j, n, n', l, m, c, p, and t are described using $|F|$, $|W|$, $|I|$, $|J|$, $|N|$, $|N'|$, $|L|$, $|M|$, $|C|$, $|P|$, and $|T|$, respectively. Hereupon, in the given numerical illustration in this study, we set $|F|=4$, $|W|=4$, $|I|=3$, $|J|=3$, $|N|=3$, $|N'|=3$, $|L|=2$, $|M|=4$, $|C|=5$, $|P|=2$, and $|T|=2$. Therefore, the presented mathematical model will have 262 binary variables, 886 linear constraints, 7 bounded variables in the range of [0, 1], 7 bounded variables in the range of [0.5, 1], and 387 positive variables. Noteworthy, considering carbon cap-and-trade and offset mechanisms will add $2|T|$ and $|T|$ positive variables to the above variables, respectively.

7 Conclusion

Increasing the environmental awareness of people, customers' tendency to buy green products, etc., have led to substantial consideration of environmental sustainability by manufacturing firms in the last decades. This study presented a novel multi-echelon, multi-product optimization-based mathematical model for a CLSCN design in which both strategic and tactical decisions are taken simultaneously into account. The model aims to minimize the total cost, total CO_2 emission, and robustness cost, simultaneously. Later, the model is extended using various carbon emission mechanisms (i.e., the carbon tax, cap, cap-and-trade, and offset policies). A RMFPP version of the original model is also devised to deal with soft constraints and epistemic uncertainty of the main input parameters. A benchmarked numerical example in the electronic industry is utilized to validate the efficiency and practicality of the developed models. Afterward, the well-known TH approach is exploited in order to deal with the presented three-objective optimization model. The obtained results indicate that the presented OFs are in conflict with each other in such a way that improving one OF will lead to worsening other OFs and vice versa. This issue

Table 6 Complexity of the crisp mathematical model

Variables	Positive	$\|P\|.\|T\|.((\|M\|.(\|F\|+\|J\|)+\|F\|)+\|L\|.(\|F\|.\|W\|+\|W\|.\|C\|+\|C\|.\|I\|+\|I\|.\|J\|+\|W\|.\|J\|)+\|W\|+\|J\|)+2\|N\|.(2\|W\|+\|F\|+\|I\|+\|J\|)$
	Binary	$\|N\|.(\|F\|.(1+\|J\|.\|N'\|)+\|W\|+\|I\|+\|J\|)+\|P\|.\|M\|.\|T\|.(\|F\|+\|J\|)$
	Bounded [0, 1]	7
	Bounded [0.5, 1]	7
Constraints	Linear	$\|P\|.\|T\|.(\|J\|.(5+\|M\|)+\|F\|.(4+\|M\|)+2\|C\|+\|W\|+\|I\|)+2\|F\|.\|J\|.\|N.\|N'\|+(\|F\|+\|W\|+\|I\|+\|J\|).(1+\|T\|)+6\|N\|.(\|F\|+2\|W\|+\|I\|+\|J\|)$

approves the necessity of the formulation of the problem as a multi-objective model. It is then followed by carrying out several sensitivity analyses on the TH approach's main parameters. Thereafter, a comparative study between different carbon emission policies is performed whose results reveal that choosing the best policy highly depends on to the preference of the DM(s); however, the cap-and-trade policy could be suggested in the problems similar to the structure of the concerned problem in this paper. Finally, we carried out some sensitivity analyses on the carbon buying/selling and cap size parameters in the selected mechanism (i.e., the cap-and-trade policy). Finally, we elaborated on the complexity of the developed optimization model in terms of the number of constraints, binary, positive, and bounded variables. It should be noted that the time-consuming process of data gathering, relying on some old data due to the lack of access to new ones, and finally implementing and confirming the efficiency of the developed mathematical model only using a case study/numerical illustration in the copier industry and ignoring other industrial sectors could be considered as the limitations of the present study.

Developing the presented network by considering other echelons (e.g., suppliers, cross-docks), utilizing other types of uncertainty handling approaches (e.g., stochastic programming and mixed fuzzy-stochastic programming) are some other avenues for further research that could be followed in the future researches. Furthermore, considering geological features of the candidate sites used for establishing the facilities, taking into account uncertainties in other parameters of the mathematical model (such as the proportion of products returned), considering issues related to risk management (such as the resilience of the designed SC network), accounting for social aspects of sustainability (e.g., job creation, social equity, etc.), applying similar mathematical models to other electronic devices and other industries, and finally proposing an efficient solution algorithm for solving the large-sized problem instances within a reasonable computation time are other interesting future research avenues.

Appendix

Sets	
$p \in P$	Index of products
$f \in F, j \in J, w \in W, i \in I$	Index of locations for opening MCs, RCs, WHs, and DCs
$c \in C$	Index of customers
$n, n' \in N, N'$	Index of available capacity levels
$l \in L$	Index of available transportation modes
$t \in T$	Index of time periods.

Parameters	
d_{cpt}	Forcasted demand of end-user c for product p in period t
$t^1_{pfwlt}, t^2_{pwclt}, t^3_{pcilt}, t^4_{pijlt}, t^5_{pjwlt}$	Unit shipment cost of product p from MC f to WH w, from WH w to end-user c, from end-user c to DC i, from DC i to RC j, and from RC j to WH w, using transportation mode l in period t

$r^1_{fw}, r^2_{wc}, r^3_{ci}, r^4_{ij}, r^5_{jw}$	Distance between MC f and WH w, WH w and end-user c, end-user c and DC i, and DC i and RC j
$f^1_{fn}, f^2_{wn}, f^3_{in}, f^4_{jn}$	Fixed cost of establishing MC f, WH w, DC i, and RC j with capacity level n
$v^1_{pft}, v^2_{pwt}, v^3_{pct}, v^4_{pit}, v^5_{pjt}$	Unit production, holding, collection, disassembly, and remanufacturing cost of product p, in the MC f, in the WH w, from end-user c, and in the RC j in period t
$s_{fnjn'}$	Saving cost of establishing MC f with capacity level n and RC j with capacity level n' at the same location ($f=j$)
δ, p^+, p^-, p^0	The carbon tax rate per unit, buying price, selling price, and offset price per kg in the carbon market
$h^1_{fn}, h^2_{wn}, h^3_{in}, h^4_{jn}$	Production capacity of MC f, processing capacity of WH w, disassembling capacity of DC i, and remanufacturing capacity of RC j with capacity level n
C^{cap}	The imposed carbon allowance
α_p	Minimum percentage of product p returned from a end-user
α'_p	Minimum percentage of product p that could be remanufactured
$e^1_{pf}, e^2_{pw}, e^3_{pi}, e^4_{pj}, e^5_{pl}$	CO_2 emitted per manufacturing each unit of product p in MC f, holding each unit of product p in WH w, disassembling each unit of product p in DC i, remanufacturing each unit of product p in RC j, and transporting each unit of product p from a facility to an adjacent facility via transportation mode l

Decision variables	
$x^1_{fn}, x^2_{wn}, x^3_{in}, x^4_{jn}$	1, if a MC, WH, DC, and RC is established at its potential location with capacity level n, otherwise 0
o_{pft}	Quantity of product p manufactured in MC f in period t
$q_{pfwlt}, u_{pwclt}, w_{pcilt}, y_{pijlt}, z_{pjwlt}$	Quantity of product p transferred from MC f to WH w, from WH w to end-user c, accumulated from end-user c and shipped to DC i, and from DC i to RC j using transportation mode l in period t
I_{pwt}	Inventory level of product p at WH w at the end of period t
δ^-_t, δ^+_t	The quantity of carbon credit sold, purchased in period t

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