Computers & Industrial Engineering 157 (2021) 107326

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

A hybrid modeling approach for green and sustainable closed-loop supply chain considering price, advertisement and uncertain demands

Behrooz Khorshidvand [a], Hamed Soleimani [a,b,*], Soheil Sibdari [c], Mir Mehdi Seyyed Esfahani [d]

[a] Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
[b] School of Mathematics and Statistics, University of Melbourne, Melbourne, Parkville, VIC 3010, Australia
[c] Charlton College of Business, University of Massachusetts, Dartmouth, USA
[d] Faculty of Industrial Engineering and Management Systems, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

ARTICLE INFO

Keywords:
Closed-loop supply chain
Supply chain coordination
Supply chain network design
Robust optimization
Lagrangian relaxation
Uncertain demand

ABSTRACT

The closed-loop supply chain network design (CLSCND) has garnered a lot of attention since it can handle economic and environmental issues. Likewise, supply chain coordination (SCC) tools can play an important role in enhancing the performance of the supply chains. This paper proposes a new hybrid method, in which SCC decisions and CLSCND objectives are simultaneously involved. First, this approach makes price, greenness, and advertisement decisions, and then it aims at maximizing profit and minimizing CO_2 emission. A new nonlinear programming (NLP) model is developed based on the sensitivity of the return rate to green quality and the customers' maximum tolerance, while the demands are uncertain. In order to overcome the uncertain demands, a robust optimization (RO) model is used. A Lagrangian relaxation algorithm is also employed to solve large-scale instances in a logical running time. The applicability of the proposed approach is corroborated through several examples. The results indicate an improvement in the performance of economic and environmental objectives under greening and advertising decisions. Furthermore, the proposed RO model outperforms the model that does not consider a robust approach.

1. Introduction

Nowadays, green and sustainable supply chains enable businesses to follow environmental regulations and provide competitive products or services (Sauer and Seuring, 2019; Zhen et al., 2019). At the outset, the economic aspects of supply chains played a central role in the network configuration. Due to growing environmental concerns, green aspects have become a trend among experts (Nayeri et al., 2020). Closed-loop supply chain (CLSC) improves the sustainable performance of networks by focusing on forward and backward flows (Guide Jr and Van Wassenhove, 2009). A well-organized CLSC helps companies meet the tradeoff between increasing profits and reducing emissions (Kazemi et al., 2019). Moreover, a CLSC contains a multi-level network to optimize the product's value in the forwarding logistics and a returned product's value in the reversing logistics. This configuration simultaneously focuses on the supply, manufacturing, distribution, and retail centers to produce and deliver specific products. Then, it focuses on collection, reconditioning, disassembly, and disposal centers to collect, refurbish, or dispose of the returned products (Govindan et al., 2015; Prajapati et al., 2019).

The relevant literature indicates that carbon emission is a universal environmental factor that scholars generally consider (Zhen et al., 2018). Supply chains are considered the potential source of CO_2 emission, which causes global warming (Ahmed and Sarkar, 2018). Thus, many studies have focused on reducing the adverse environmental effects of supply chains, particularly CO_2 indicator, representing companies' carbon footprint (Haddad-Sisakht and Ryan, 2018; Hickman and Banister, 2011). Companies can produce CO_2, directly and indirectly, when using some raw materials or components, establish new facilities or develop existing facilities, and transport products (Ahi and Searcy, 2015). There is a direct relationship between emissions and opening facilities and transportation. The total amount of carbon dioxide that is a numerical quantity is called a carbon footprint. To mitigate CO2 emission, companies try to balance their economic and environmental objectives concerning emission rates, capacities, and costs (Mallidis et al., 2012). In response to the effects of CO_2 emission, the green and

* Corresponding author at: Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran.
E-mail addresses: behrooz.khorshidvand@qiau.ac.ir (B. Khorshidvand), hamed.soleimani@unimelb.edu.au (H. Soleimani), ssibdari@umassd.edu (S. Sibdari), msesfahani@aut.ac.ir (M. Mehdi Seyyed Esfahani).

https://doi.org/10.1016/j.cie.2021.107326
Received 28 July 2020; Received in revised form 6 March 2021; Accepted 12 April 2021
Available online 15 April 2021
0360-8352/

sustainable closed-loop supply chain (GSCLSC) has become known as the most promising solution.

Generally, green aspects are now playing a pivotal role in supply chains. Thus, green supply chain management has increasingly been used to satisfy the related objectives (Zailani et al., 2012). According to the relevant literature, the greenness of green products reflects their emission savings (Hong and Guo, 2019). Indeed, an indirect relationship has been shown between green products and emissions. Similarly, greenness positively impacts profitability because supply chains can attract more demand when supplying green products (Liu and Yi, 2017).

Looking from a company-image perspective, the role of advertising in supply chains has been on the rise. Investing in advertisement can be considered as an enabler for improving the image of and the demand for products. Thus, supply chains use various policies to create a synergy by considering multiple tools, such as advertising and greening (Heydari et al., 2018). The coordinating decisions focus on necessary tradeoffs between a number of significant factors, i.e., pricing, green quality, and sales effort decisions (Alamdar et al., 2018).

On the other hand, pricing is a complicated procedure whereby sales channels decide on the price of different products, e.g., new products' price and reconditioned products' price. In this regard, there are influential factors, such as price elasticity and cross-price sensitivity, affecting the number of final customers. Many studies have developed pricing approaches based on different assumptions in dynamic and static environments (Liu and Yi, 2017; Sibdari and Pyke, 2014). Supply chains should incorporate factors that positively impact the attracted demand, such as green products and advertisement. Customers pay more attention to green products and are influenced by new advertising modes, e.g., social networks. Thus, the simultaneous use of these factors, i.e., pricing, greening, and advertising, seems necessary to make the conditions applied in academic research closer to real-world cases.

Today, market trends reflect an interrelation among critical factors, such as pricing, advertising, greening, etc. Although the price lets customers know whether a product is worth their investment and time and determines the value of a product for a company to make and for consumers to use, there are different types of elasticity that directly or indirectly impact both the pricing decision and the attracted demand. For instance, customers' behavior shows that they prefer to pay for green products since they positively impact society. Along similar lines, advertising targets the final demand by focusing on competitive advantages, e.g., greenness.

Furthermore, uncertainty is an inherent part of the supply chain in real situations, and it can pose serious decision-making problems. There are several methods for tackling uncertainty according to the conditions and the nature of the uncertain parameters (Ghelichi et al., 2018). In terms of the availability of data, uncertainty can be classified into three types. The first is deep uncertainty due to the lack of information to estimate the objective or subjective probability/possibility of plausible future situations. Robust optimization approaches can be used to overcome this type of uncertainty. The second is the randomness uncertainty of the input data due to the random nature of the parameters. Robust scenario-based stochastic programming models can be employed to deal with this type of uncertainty. The third involves epistemic uncertainty due to insufficient or unreliable data about the input parameters. Robust possibilistic programming is considered for this situation (Bairamzadeh et al., 2018). However, uncertain demands have dramatically increased in CLSC studies, especially in forward chains (Zhen et al., 2019). In real situations, customer demand is one of the most common uncertain parameters. Due to the lack of sufficient information about the probability distribution of the demand, and the presence of various scenarios for the demand volume, this parameter can be characterized by the randomness uncertainty. As noted earlier, a robust scenario-based stochastic programming model can be utilized to deal with this uncertainty.

Based on the abovementioned issues, there are specific shortcomings in the context of green and sustainable closed-loop supply chain network design (GSSCND) and supply chain coordination (SCC). In general, these two subjects have been developed separately, and the development of a simultaneous procedure has been neglected. Moreover, the combination of pricing, greening, and advertising decisions has not been broadly developed despite the fact that they can certainly create a synergic effect on various aspects of supply chains. These factors also bring academic research closer to real cases. To the best of our knowledge, this paper is one of the few studies that try to respond to the key question of whether a hybrid approach improves economic and environmental objectives through optimal coordinating decisions when there is some level of uncertainty.

The main contributions of this study can be summarized as follows:

- Considering GSCLCS and SCC objectives at the same time using a hybrid approach.
- Developing an NLP model based on the sensitivity of the return rate to green quality.
- Considering maximum tolerance with respect to green quality.
- Simultaneously incorporating pricing, greening, and advertising decisions.

As a result, this paper presents a hybrid modeling approach for GSCLSC network design based on pricing, greening, and advertising under demand uncertainty. To do so, optimal levels of pricing (for both new and reconditioned products), greening, and advertising are derived in the initial phase. Then, in the second phase, the optimal profit and emission objectives are determined based on the results of the previous phase. In order to validate the approach, a number of numerical examples are used at different scales. Moreover, to deal with large-scale instances, a Lagrangian relaxation algorithm is adjusted and utilized. Finally, managerial insights are discussed.

The rest of this paper is organized as follows: The literature review and gap identification are presented in Section 2. The problem is described in detail in Section 3. The mathematical models are formulated in Section 4. Section 5 is devoted to providing the solution approaches. Section 6 describes computational results to validate the proposed hybrid approach and solution methods. The practical implications and the sensitivity analyses are discussed in Section 7. Finally, conclusions and future studies are presented in Section 8.

2. Literature review

This section presents the literature review in two main parts. The first part is devoted to the SCC, while the second part deals with CLSC and uncertainty. Finally, the research gap is identified.

2.1. Supply chain coordination

2.1.1. Coordination based on the range of centralization and selling channels

Considering the importance of performance in supply chains, many researchers have tried to present different structures for the SCC. Due to the growing competitiveness and the development of borderless markets, supply chains are forced to update their structures based on a grade of centralization for quick response to variable demands (Thomas and Griffin, 1996; Hu et al., 2018). Firms have been trying to deal with the best potential contracts, such as revenue-sharing, to present the bases for sharing contracts in arranging the supply chain's incentives by distinguishing the optimal utilization of these contracts (Krishnan and Winter, 2011).

Furthermore, networks can define different selling channels to better focus on various customer segments. Different configurations are available for selling channels due to the growing use of the internet and online channels (Heydari et al. 2018; Xie et al., 2017). Moreover, supply chains are coordinated based on different levels of centralization, i.e., they can be organized as centralized, decentralized, or a point between these two extremes (Giannoccaro, 2018).

Table 1
The comparison of this study with the relevant papers of coordinating supply chain.

Author(s) - Year	Decision variables			Structure	Sharing approach
	Price	Green	Advertisement		
Alamdar et al., 2018	✓			DC, C	Revenue sharing
Heydari et al., 2018	✓	✓		DC, C, CO	Revenue sharing
Parsaeifar et al., 2019	✓	✓		DC, C, CO	Revenue sharing
Wang and Song, 2020	✓	✓		DC, C, CO	Profit sharing
Wang et al., 2020	✓			DC, C, CO	Revenue sharing
Xiao et al., 2019	✓		✓	DC	Cost sharing
Zhang et al., 2019	✓	✓		DC, C	Revenue sharing
Farshbaf-Geranmayeh and Zaccour, 2020	✓		✓	DC	Cost sharing
Liu et al., 2020	✓			DC, C	Profit sharing
Mondal and Giri, 2020	✓	✓		DC, C	Cost sharing
This paper	✓	✓	✓	**C**	**Revenue sharing**

Note: DC (Decentralized SC), C (Centralized SC), CO (Collaborative SC)

Ranjan and Jha (2019) defined a dual-channel supply chain to sell two types of products based on their quality. They considered two price levels for green and non-green products, and showed that this structure efficiently increased attracted demand, and consequently supply chain profit. Wang et al. (2020) considered a green network to develop pricing decisions in two selling channels. They formulated their selected network based on centralized and decentralized structures, showing that a higher level of centralization could lead to more profit for the entire chain. They also proposed a collaborative arrangement to satisfy all the entities. Zhang et al. (2019) coordinated a dual-channel (i.e., online and offline channels) CLSC based on the quality of the products and the return rates. Moreover, they considered the revenue-sharing coordination contract. They related the rate of return to the quality of products in their modeling, and optimized their models under centralized, decentralized, and collaborative structures. Wu et al. (2018) designed a two-echelon supply chain containing one supplier and two manufacturers under competition, showing the effects of the capacity constraint and supplier pricing decisions on the manufacturer's information sharing. Heydari et al. (2018) presented a three-level supply chain to calculate pricing and green quality decisions. They modeled a dual-channel (i.e., online and traditional) network through centralized and decentralized structures. They concluded that a centralized configuration could gain more profit compared to a centralized one, while leading to a loss for some entities. Thus, a collaborative configuration has been sufficiently developed to compensate for this disadvantage.

2.1.2. Green products and advertising

Green products play a crucial role in increasing attracted demand. Therefore, supply chains should invest in developing the green aspects of their products. The increased requirements can lead to a considerable revenue for them. Surveys show that around 66% of consumers are interested in buying green products (Agi and Yan, 2019). On the other hand, advertising also plays a pivotal role in gaining more income for targeted products. Targeted advertising can improve the company's share of the market. In particular, when quality is hard to evaluate before purchasing or is not competitive enough compared to new products, SCs can employ advertising to raise the product's image and demand (Farshbaf-Geranmayeh and Zaccour, 2020). Wang and Song (2020) proposed a dual-channel structure in terms of greening investment and sales efforts when customer demand is uncertain. They separately developed selling channels for green and non-green products, and they pointed out the advantages of the centralized, decentralized, and collaborative structures. Mondal and Giri (2020) provided a CLSC under greening levels and sales efforts. They formulated the models through both centralized and decentralized structures and by considering a cost-sharing contract. Liu and Yi (2017) incorporated advertising policies and green products. Their main contribution involved the effects of data on advertising, greening, and pricing policies. Xie et al. (2017) coordinated advertising levels in a CLSC network. They managed to derive the optimal values of online and offline prices for retailers, as well as wholesale prices.

Table 1 compares the current study with the related SCC papers.

In Table 1, the related papers are compared based on decision variables, including price, greenness, and advertisement, the studied and modeled structures (i.e., decentralized, centralized, and collaborative), and sharing contracts, such as revenue-sharing, cost-sharing, and profit-sharing contracts.

Accordingly, this study tries to determine the optimal levels of greening, advertising, and pricing based on a centralized structure and a revenue-sharing approach.

2.2. Supply chain network design

2.2.1. Closed-loop supply chain

CLSC has attracted much academic attention in a way that different models and solution methods have been developed to optimize these networks as much as possible (Ma and Li, 2018). CLSCs focus on three significant decisions, i.e., strategic decisions, tactical decisions, and operational decisions (Souza, 2013; Govindan et al., 2017). Two of the main advantages of using CLSCs include (i) increasing the created values of the products within their life cycle to address the demands of the customers, and then (ii) collecting returned products at their end of life phase because of their age, and physical or soft flaws, and determining the best ways to manage them (Govindan and Soleimani, 2017).

Zhen et al. (2018) designed a CLSC with forward and reverse directions under uncertain demands. They considered two types of products, i.e., new and returned products. They assumed capacity constraints for distribution locations, and developed a two-stage mixed-integer nonlinear programming (MINLP) model. Soleimani et al. (2017) provided a CLSC network design considering economic, environmental, and social concerns. They formulated a multi-objective mixed-integer linear programming (MILP) model, and solved it using a genetic algorithm for large-scale instances. Polo et al. (2019) introduced a CLCS network for integrating financial risks in the uncertainty of demands for final products; they considered the RO model to cope with uncertain conditions. Haddad-Sisakht and Ryan (2018) designed a CLSC network for both new and returned products, while considering uncertainty in demands. They proposed a three-stage hybrid model that combines stochastic demands and return rates with uncertain governmental tax rates of CO_2 emissions.

So far, several solution methods have been developed to solve these networks. Typically, these methods are classified into exact methods, decomposition and relaxation methods, heuristic methods, and *meta*-heuristic methods (Schewe et al., 2020; Özkır and Başlıgil, 2013).

2.2.2. Green and sustainable supply chain

Three main economic, environmental, and social objectives have been considered in a large number of studies during the last few years. These concerns have led many authors, such as Ansari and Kant (2017) and Badi and Murtagh (2019), to present the last directions through an in-depth survey on the green supply chain management and sustainable supply chain management. In particular, environmental concerns often focus on pollutant gases, such as CO_2, that strictly depend on the

Table 2
The comparison of this study with the relevant papers of designing supply chain.

Author(s) - Year	Objective			Decisions		Multi-period	Uncertain environment	Robust approach	Solution method
	Single	Multiple	Economic	Environmental	Social				
Mohseni and Pishvaee, 2016	✓		✓			✓	✓	✓	CPLEX
Soleimani et al., 2017		✓	✓	✓	✓	✓	✓		Genetic algorithm
Jahani et al., 2018	✓		✓			✓			Branch and cut
Zhen et al., 2018	✓		✓				✓		CPLEX
Diabat et al., 2019		✓	✓		✓	✓	✓	✓	Lagrangian relaxation
Polo et al., 2019	✓		✓			✓	✓	✓	CPLEX
Zhen et al., 2019		✓	✓	✓			✓		Lagrangian relaxation
Hamdan and Diabat, 2020		✓	✓			✓	✓	✓	Lagrangian relaxation
Shen, 2020		✓	✓	✓			✓		LINGO
This paper		✓	✓	✓		✓	✓	✓	**Lagrangian relaxation**

establishment of facilities and vehicle transportation, as well as production and storage of items (Phouratsamay and Cheng, 2019; Ahli and Searcy, 2015). Moreover, sustainability concerns focus on simultaneously balancing the financial, environmental, and social objectives (Soleimani et al., 2017).

Ghaderi et al. (2018) designed a sustainable network model based on economic, environmental, and social objectives. They considered some major components to model ecological impacts, including opening facilities, production, inventory, and transportation. Zhen et al. (2019) designed a CLSC considering greenness and financial objectives with uncertain demands. They offered a multi-objective MILP model considering a scenario-based approach under an uncertain environment. They considered greening decisions in the opening, transporting, and the quality level of facilities.

2.2.3. Uncertainty in the design of supply chain networks

Real-world systems often deal with noisy and incomplete data. For instance, financial flows, customer demands, the consumption of energy, and other resources are some examples of uncertain data (Mulvey et al., 1995). Thus, the RO theory has been developed to cope with these uncertain situations and allow identifying the optimal solution (Ben-Tal and Nemirovski, 2008). RO methods are applied for both single and multi-objective problems (Hamdan and Diabat, 2020). Uncertain demand has a significant effect on supply chain decisions, and all involved facilities have to take responsibility to satisfy their customers. These uncertainties increase based on different predicted (e.g., seasonal demands) and unpredicted (e.g., the COVID-19 pandemic) patterns.

According to Peng et al. (2020), uncertainty factors are classified into four groups, i.e., (i) parameter uncertainty, which is mainly targeted at randomness, (ii) background uncertainty, (iii) CLSC model's structure uncertainty, and (iv) CLSC model's result uncertainty. Thus, in order to handle the uncertainty factors in the CLSC and to enhance the sustainable development of the economy, it is critical to identify different sources of uncertainty, and then design approaches for modeling them.

Also, Peidro et al. (2009) classified uncertainty modeling approaches into four main classes, including (i) analytical methods, (ii) models based on artificial intelligence, (iii) models based on simulation, and (iv) hybrid methods. Analytical methods include robust optimization, stochastic programming, game theory, and fuzzy programming. Among analytical methods, robust optimization, stochastic programming, and fuzzy programming are most commonly used to deal with uncertainty.

Moreover, the RO model has gained attention because it yields applicable outputs, while it is flexible in dealing with risks and uncertainties in real-world optimization problems (Pishvaee and Khalaf, 2016; Bairamzadeh et al, 2018). Likewise, the RO model provides a compelling procedure for modeling uncertainty in many areas, such as supply chain management. The RO model is efficiently used to address uncertain parameters, and it gives insights for strategic, tactical, and operational planning related to plants, distribution centers, quantity shipped, and demand fulfillment (Prakash et al., 2020).

Govindan et al. (2020) proposed a hybrid approach for selecting a circular supplier, as well as designing a CLSC under uncertain circumstances. They considered uncertainty in both multi-criteria decision making and MILP modeling, and used the fuzzy theory to overcome uncertainty. Yu and Solvang (2020) introduced a new fuzzy-stochastic multi-objective model for an SCLSC. They showed that the flexibility and rationality of the decision making on transportation handling, demand allocation, and facility operations could be significantly enhanced. Prakash et al. (2020) formulated a new integrated RO model for designing the CLSC network under risk and demand uncertainty. They confirmed the RO's applicability through a real case.

Diabat et al. (2019) designed a supply chain network for perishable products considering reliability and disruption domains. Moreover, they considered uncertain product demands, and defined various scenarios to demonstrate the variations in such demands. Furthermore, they developed an RO model based on maximum regret as a variability measure. They solved the RO model using the Lagrangian relaxation algorithm to deal with large-scale instances. Their results proved the efficiency of the RO model in comparison to the lack of the RO theory. Mohseni and Pishvaee (2016) provided an RO model for a biofuel supply chain in terms of two norms of the uncertain data vector. In this study, the authors presented an RO framework based on Ben-Tal and Nemirovski (2008) to convert their decision space to a convex polyhedron. The results show that the RO model does not increase the running time of the problem. Moreover, this strategy leads to a significant reduction in production costs.

Hamdan and Diabat (2020) designed a supply chain for dealing with the risk of disruptions; they developed their model based on Aghezzaf et al. (2010), and then extended it using the Lagrangian relaxation algorithm to minimize delivery time and cost. Heidari-Fathian and Pasandideh (2018) designed a green network for blood SC using an RO model. As their MILP model was complicated and NP-hard, they proposed a Lagrangian relaxation algorithm to solve large-scale instances within a reasonable timeframe. Using a computational study, they proved the competency of this algorithm in reaching an exact bound with a small gap. Ghaderi et al. (2018) proposed a multi-objective RO approach that was able to model the performance of the SC and maintain both the optimality and feasibility in a robust manner. They also showed that their proposed RO model outperformed the deterministic model based on the mean and standard deviation measures.

Table 2 compares the current study with the relevant papers that focus on designing supply chains.

According to Table 2, the related studies are compared in terms of being single or multi-objective, the domain of sustainable decisions (i.e., economic, environmental, and social), the number of periods, uncertainty environment, robust approach, and solution methods. Consequently, this paper focuses on the multi-objective model, including economic and environmental concerns in a multi-period and uncertain

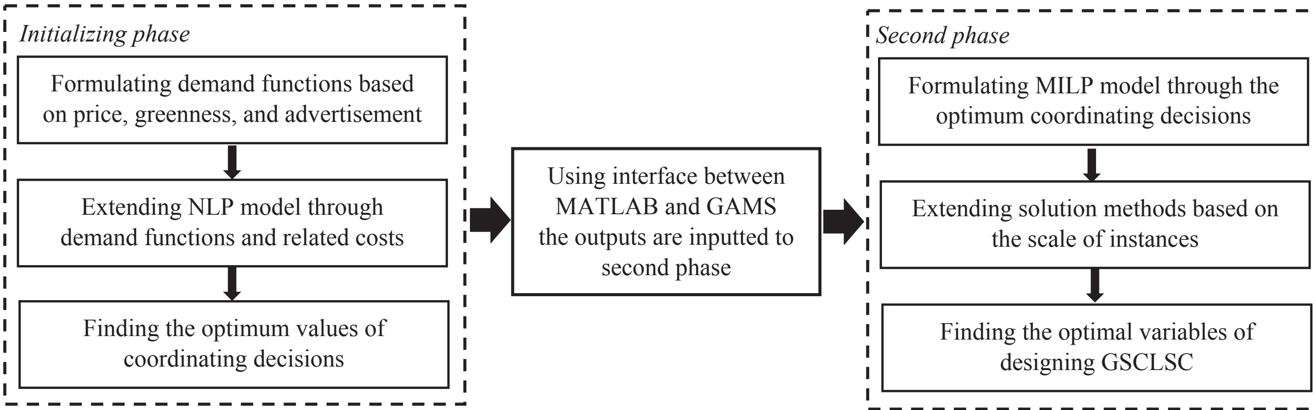

Fig. 1. The proposed hybrid approach.

environment. The RO model is used to deal with demand, while the Lagrangian relaxation algorithm is developed based on the rough constraint of the uncertain demand.

2.3. Gap identification

Upon reviewing the available literature, it can be said that while a number of studies have described the coordination issues and many others have discussed the concerns related to the network design, there still exists a lack of enough effort to consider these two sets of vital issues at the same time. To the best of our knowledge, the following shortcomings are in the relevant literature. Firstly, many SCC studies have neglected the synergy effect created by simultaneous attention to greening and advertising levels on increasing customers' demands. This study develops a new NLP model based on greening, advertising, and pricing decisions, where customers' behavior is sensitive to the green quality of products. Likewise, to attract more demands for the reconditioned products, the advertising policy is utilized. Indeed, the advertisement should highlight some critical factors, such as competitive pricing and greening aspects. In total, the modeling of the initializing phase benefits a synergic effect by a combination of pricing, greening, and advertising to increase the total profitability of the studied supply chain. It should be noted that the uncertainty of demands is also considered using the expected potential demand in this phase.

Secondly, the impact of SCC tools on the performance of CLCSND has not been well-developed. Thus, this study is the first to present a new hybrid approach to consider coordination tools, i.e., pricing, greening, and advertising, along with network design objectives under demand uncertainty.

As a result, the main contributions of this study are highlighted as follows:

- Providing a new hybrid modeling approach for a GSCLSC under uncertain demands.
- Incorporating the maximum tolerance concerning the greening level that encourages supply chain entities to provide green products.
- Extending an NLP model in terms of the sensitivity of the return rate to green products.
- Optimizing SCC objectives and GSCLSC objectives at the same time.

3. Problem definition

3.1. Hybrid approach

This study, as an innovation, presents a hybrid approach to consider the SCC decisions and the SCND objectives in an integrated framework and demands' uncertainty. In the initializing phase, the major decisions including the pricing of the new and reconditioned products along with the optimal level of greening and advertising are derived. Then, using the optimal values of the first phase, the MILP model is solved to find the optimal economic and environmental objectives.

Fig. 1 depicts the proposed hybrid approach as follows.

According to Fig. 1, in the initializing phase, the optimal variables of pricing, greening, and advertising through an NLP model and their optimal equations are derived; then, in the second phase, the SCND decisions are made on the optimal values of the coordination decisions.

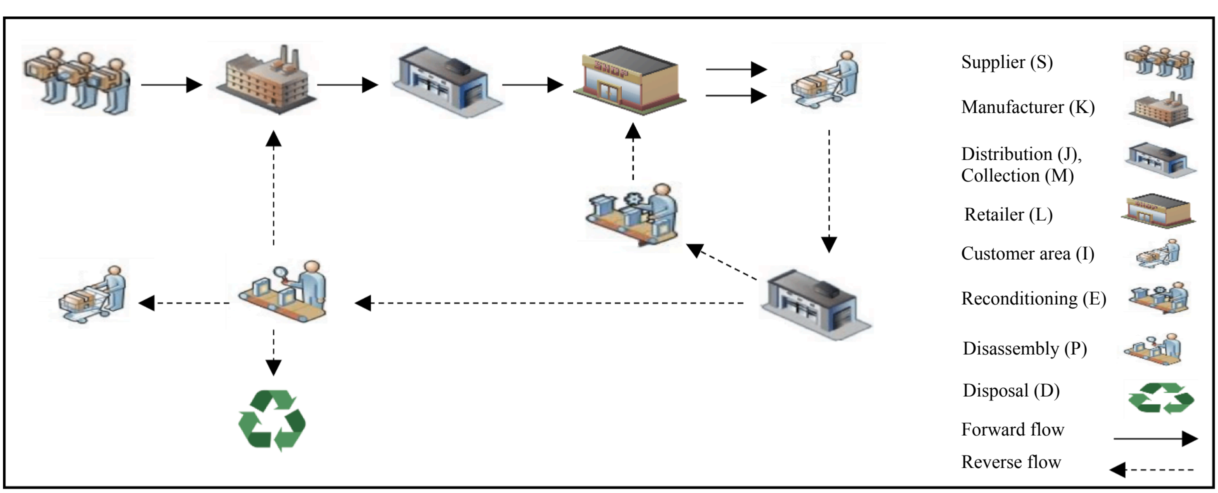

Fig. 2. The schematic of the studied network.

In general, the pseudo-code used to solve the SCC problem in the first phase, along with the GSCLSC problem in the second phase is described below.

Algorithm 1. (: *Hybrid SCC and GSCLSC*)

```
{Initializing phase: MATLAB}
data 1: ℓ, E(ρ), v, c, k_c, k_r, k_n, k_a, A, delta
begin
begin
solve Eq. (4);
solve Eq. (5);
solve Eq. (6);
solve Eq. (7);
end
results 1: G, Ad, PN, PR
{Second phase: GAMS}
data 2: GDXIN (results 1) Interface between MATLAB & GAMS
GSCLSC data
begin
solve Eq. (46) with Lagrangian relaxation and subgradient algorithm
end
results 2: F_xytw, R_xytw, θ'_xtw, θ''_xtw, ϑ_xtw, I_xtw, Z_xt
end
```

3.2. Studied supply chain network

This study presents a multi-level, multi-channel, multi-period GSCLSC problem in which two main objectives of profit-maximization and emission-reduction are studied. Due to the presence of multiple levels including supply, distribution, manufacturing, retail, collection, reconditioning, disassembly, and disposal centers, the multi-level model is developed. As two types of new and reconditioned products are sold, dual selling channels are developed to sell them separately. Plus, a selling channel is opened to sell the component by disassembly centers where the sale price is equal to the buying price of components from suppliers. Fig. 2 portrays the schematic of centers and flows in the studied network.

According to Fig. 2, the manufacturer receives the required components from both disassembly and supply centers and then produces the new product in the predefined quality level and transports to distribution centers. Afterward, the distribution center has two primary responsibilities; first, allocate the new product to retail centers based on their demands and keep the inventory to cope with unexpected market demands. Accordingly, the distributor is responsible for handling the retailers' inventory for the new product through coordinated decisions such as vendor managed replenishment strategy. Next level, the retailer should sell the new product which deliver from distribution centers and sell the reconditioned product which delivered from reconditioning centers. These products are sold via dual-channel by retailers. Besides, the retail centers can do a predefined advertising level to tempt customers to purchase the reconditioned product. When customers return products because of life-cycle ending or physical and soft damaging, the collection center receives them and separates based on their quality and send the repairable products to recondition centers, and the remaining are sent to disassembly centers. In addition to supplying components by the disassembly center, it sells a share of them to the secondary market and sends the remaining to disposal centers.

Consequently, this study tries to find the optimal values of pricing for the new and reconditioned products, greening, and advertising level via an NLP model and equilibrium equations in the first phase and then formulate and optimize a multi-objective MILP for SCND objectives, including profit-maximization and emission-minimization, in the second phase.

The assumptions of this study are mentioned as follows.

- The studied SC is considered under the centralized structure in which there is one unite of decision making.
- Due to the centralized structure, there is no competition between the facilities of each level.
- The quality and price of reconditioned products are the same.
- All of the new products are fabricated with the same green quality.
- The advertising level only applies to promote the recondition product.
- There is no limitation on the number and capacity of vehicles for transportation.
- All of the facilities that are decided on the opening of them are capacitated.

3.3. Notations

The CLSC network is denoted by $\mathscr{G}(\mathscr{N},\mathscr{A})$, where $\mathscr{N}$ is the set of nodes and $\mathscr{A}$ is the set of arcs. The node set $\mathscr{N} = \mathscr{F} \cup \mathscr{R}$, where $\mathscr{F}$ is a set of potential facilities consisting of manufacturing centers K, distribution centers J, retail centers L, collection centers M, reconditioning centers E, and disassembly centers P. Therefore, $\mathscr{F} = K \cup J \cup L \cup M \cup E \cup P$. Also, $\mathscr{R}$ is the set of customer areas I, and secondary customer areas Q; i.e., $\mathscr{R} = I \cup Q$. The arc set $\mathscr{A} = \mathscr{Z} \cup \mathscr{U}$, where $\mathscr{Z}$ is the arc set of forward logistics; i.e., $\mathscr{Z} = \{xy : (x \in S, y \in K), (x \in K, y \in J), (x \in J, y \in L), (x \in L, y \in I)\}$, and $\mathscr{U}$ is the arc set of reverse logistics; i.e., $U = \{xy : (x \in I, y \in M),$

$(x \in M, y \in E), (x \in E, y \in L), (x \in L, y \in I), (x \in M, y \in P), (x \in P, y \in D),$

$(x \in P, y \in K), (x \in P, y \in Q)\}$. See Fig. 2 for the network topology.

In order to clarify, the notations used in this study are represented as follows.

3.3.1. Sets and indices

Set	Description
S	Set of supply centers
K	Set of manufacturing centers
L	Set of retail centers
M	Set of collection centers
E	Set of reconditioning centers
P	Set of disassembly centers
D	Set of disposal centers
J	Set of distribution centers
I	Set of customer areas
Q	Set of secondary customer areas
T	Set of periods, indexed by both t and t'
W	Set of scenarios, indexed by w

3.3.2. Parameters

Parameter	Description
DIS_{xy}	City block distance between node x and node y, where $x, y \in \mathscr{A}$
TC	Transportation cost rate
FC_x	Fixed cost of opening facility x in each period, where $x \in \mathscr{F}$
PC_x	Cost rate of processing by facility x, where $x \in \mathscr{F}$
SC	Average cost rate of unmet demands and discarded products
HC	Holding cost rate per unit of product
AC	Advertising cost rate
RC	Penalty-reward rate
TE	Unit CO_2 emissions of transporting one truck-load of (returned) products per kilometer
TC	Unit cost of transporting one truck-load of (returned) products per kilometer
FE_x	Fixed CO_2 emissions from opening facility x, where $x \in \{K \cup E \cup P\}$
CAP_x	Capacity of facility x, where $x \in \mathscr{F}$
D'_{xtw}	Customer demand x for new product in period t under scenario w, where $x \in I$
D''_{xtw}	Customer demand x for reconditioned product in period t under scenario w, where $x \in I$

(continued on next page)

(*continued*)

Parameter	Description
D_{xtw}	Secondary demand x for components in period t under scenario w, wherex $\in Q$
δ	Factor for converting a unit of product to the unit capacity in facilities
δ'	Factor for converting a unit of returned product to the unit capacity in facilities
ζ	Factor for converting a unit of component to new product
ζ'	Factor for converting rate of return product to component
α	Rate of recoverable products
β	Rate of returning components to manufactures
β'	Rate of selling components to secondary customers
τ	Rate of advertising level per product
τ'	Rate of greening level per product
Y	Desirable value for disassembling
σ	Percentage of returned products
α	Percentage of reconditioned products
P'	Buying price of components from external suppliers
P''	Buying price of return products
PCO	Selling price of components to secondary customers
ℓ	Share of new products from potential demand
$E(\rho)$	Expected potential demands (new products + reconditioned products)
v	Average cost of preparing per product
c	Greening cost coefficient
k_c	Cross-price sensitivity in (reconditioned) new products channel
k_r	Price elasticity of demand for reconditioned product channel
k_n	Price elasticity of demand for new product channel
k_a	Advertising elasticity of demand for reconditioned product channel
A	Maximum tolerance when G is zero
delta	Sensitivity of return rate to green quality
$\mathscr{Y}_w$	Probability of scenario$w$
B	Maximum allowable number of opened facilities

3.3.3. Decision variables

Decision variable	Description
F_{xytw}	Volume of products transported from node x to node y in period t under scenario w, wherex, $y \in \mathscr{Z}$
R_{xytw}	Volume of returned products transported from node x to node y in period t under scenario w, wherex, $y \in \mathscr{U}$
θ'_{xtw}	Volume of unmet demands of new products for customer x in period t under scenario w, wherex $\in I$
θ''_{xtw}	Volume of unmet demands of reconditioned products for customer x in period t under scenario w, wherex $\in I$
ϑ_{xtw}	Volume of discarded returns for customer x in period t under scenario w, wherex $\in I$
I_{xtw}	Inventory level of facility x at the end of period t under scenario w, wherex $\in J$
Z_{xt}	Binary variable equals "1" if facility x is established in period t, and "0" otherwise; wherex $\in \mathscr{T}$
G	Greening level of products
Ad	Targeted advertising level of reconditioned products
PN	Selling price of new products
PR	Selling price of reconditioned products

4. Mathematical models

4.1. Coordination model

As mentioned before, the studied network is designated based on a centralized structure; thus, there is not any competition among entities, and an entity can be represented to define the financial and demand flows in each echelon.

First, the demand functions of new and reconditioned products should be determined in terms of market share, price elasticity, and cross-price factors. Eqs. (1) and (2) present the demand functions for two types of products, separately.

$$D_n = [(1-\ell)\times E(\rho) - k_n \times PN + k_c \times PR] \tag{1}$$

$$D_r = [\ell \times E(\rho) - k_r \times PR + k_c \times PN] \tag{2}$$

According to the above equations, to calculate the demands of new and reconditioned products, the market share limits the expected potential demand. Due to the uncertainty of demands, the potential demand's value is also affected by different scenarios. Thus, its expected value will be replaced in the demand functions. As well, demands have an inverse relationship to price elasticity, which means increasing the price leads to reducing the related demand by a given coefficient. Besides, the price of each channel affects the demand for another channel directly. Indeed, if the price of the new product increases, the demand for the reconditioned product increases. Note that the cross-price coefficient is considered equal for both products.

Eq. (3) reformulates the whole chain's financial flow by taking into account the demand functions. Thus, the income and cost flows are inserted into an NLP model. It should be noted that the buying price of return products is given by a predefined percent of the new product's price. Also, the selling price of components is as equal as the buying price of them. Therefore, the amount of them is not considered as a decision variable and not inserted into income and cost flows.

$$\Pi_T = [PN \times D_n] + [PR \times (D_r + k_a \times Ad)] - [(D_n + D_r)\times(v \times (A - delta \times G))] - \left[a \times \frac{Ad^2}{2}\right] - \left[c \times \frac{G^2}{2}\right] \tag{3}$$

As shown in Eq. (3), the first term determines the income of selling the new product. The second term returns the income of selling the reconditioned product. Note that the advertising policy is defined to elevate the attracted demands for the reconditioned product. Thus, the advertising level adds the attracted demand of the reconditioned channel by considering its elasticity of demand. The third term indicates the cost of preparing the products considering total demand. In this term, *"delta"* shows the sensitivity of return rate to green quality and *"A"* defines maximum tolerance when *"G"* is zero. Finally, terms fourth and fifth return the cost of advertising and greening levels, respectively.

Corollary 1.. *Eq. (3) is concave. This means that its Hessian matrix satisfies definite negative conditions of concavity (Appendix A).*

Theorem 1.. *The optimal price of new and reconditioned products, as well as the optimal levels of greening and advertising.*

These optimal values are calculated as follows:

$$PN^* = {x_6}^{-1} \times \left[\frac{2k_c}{x_5}\times(\ell \times E(\rho) - v \times x_3 \times (A - x_4 \times E(\rho))) - (1-\ell) \times E(\rho) - v \times x_2 \times \left(A - x_4 \times \left(E(\rho) + \frac{x_3}{x_5}\times(\ell \times E(\rho) - v \times x_3 \times (A - x_4 \times E(\rho)))\right)\right)\right] \tag{4}$$

$$PR^* = {x_5}^{-1} \times [\ell \times E(\rho) + 2k_c \times PN^* - v \times x_3 \times (A - x_4 \times (E(\rho) + PN^* \times x_2))] \tag{5}$$

$$Ad^* = [PR^* \times x_1] \tag{6}$$

$$G^* = \frac{x_4}{delta} \times [E(\rho) + PN^* \times x_2 + PR^* \times x_3] \tag{7}$$

In addition, the values of x_1, x_2, x_3, x_4, x_5, and x_6 are computed as follows:

$x_1 = k_a \times a^{-1}$	$x_2 = k_c - k_n$	$x_3 = k_c - k_r$
$x_4 = delta^2 \times v \times c^{-1}$	$x_5 = 2k_r - k_a \times x_1 - v \times x_3^2 \times x_4$	
$x_6 = 2k_n - x_5^{-1} \times (4k_c \times v \times x_2 \times x_3 \times x_4) - v \times x_4 \times x_2^2 - x_5^{-1} \times (v \times x_2 \times x_3^2 \times x_4^2) - 4k_c^2 \times x_5^{-1}$		

Proof.. *Appendix A.*■

Corollary 2.. *According to Eq. (6), the advertising level is only dependent on the optimal price of the reconditioned product.*

Corollary 3.. *According to Eq. (7), the greening level is dependent on the price of both products.*

4.2. Green and sustainable network design model

The green-sustainable network model is formulated considering the results of the initializing phase. For this purpose, two main objectives, including economic and environmental concerns, are reformulated. The economic objective focuses on the entire revenue and costs related to the establishment of entities and the flow of products and components among entities and customers. The environmental objective also concentrates on the entire emissions related to the establishment of entities and the transportation of vehicles.

First, the economic objective is formulated in order to maximize the entire profit of the studied network. This objective includes total revenue, total fixed cost, total transportation cost, total process cost, total buying cost, total shortage cost, total holding cost, total advertising cost, total reward, and total greening cost. Eqs. (8) to (17) demonstrate these aims, respectively.

The total income *TINC* is presented as:

$$TINC=\sum_{w\in W}\mathscr{Y}_w\left\{PN^*\sum_{x\in L}\sum_{y\in I}\sum_{t\in T}F_{xytw}+PR^*\sum_{x\in L}\sum_{y\in I}\sum_{t\in T}R_{xytw}+PCO\sum_{x\in P}\sum_{y\in Q}\sum_{t\in T}R_{xytw}\right\} \tag{8}$$

According to Eq. (8), the first term determines the total revenue of selling the new product. The second term computes the revenue of selling the reconditioned product, and the last term defines all the revenue of selling the components.

The total fixed cost *TF* is reformulated as:

$$TF=\sum_{x\in\mathscr{F}}\sum_{t\in T}FC_xZ_{xt} \tag{9}$$

From Eq. (9), the total fixed cost of establishing for manufacturing, distribution, retail, collection, reconditioning, and recycling centers are measured.

The total transportation cost *TT* is also modeled as:

$$TT=\sum_{w\in W}\mathscr{Y}_w\times \mathrm{TC}\left\{\left[\sum_{x,y\in\mathscr{Z}}\sum_{t\in T}DIS_{xy}F_{xytw}\right]+\left[\sum_{x,y\in\mathscr{U}}\sum_{t\in T}DIS_{xy}R_{xytw}\right]\right\} \tag{10}$$

According to the above Equation, the transportation cost is explained concerning truck-load vehicles. Also, the cost and capacity occupied by a unit of product and returned one is distinctively specified in terms of given coefficients.

The total process cost *TP* is represented as:

$$TP=\sum_{w\in W}\mathscr{Y}_w\left\{\sum_{x,y\in\mathscr{Z}}\sum_{t\in T}PC_xF_{xytw}+\sum_{x,y\in\mathscr{U}}\sum_{t\in T}PC_xR_{xytw}\right\} \tag{11}$$

As defined in Eq. (11), the process cost for each entity is independently measured in terms of its related tasks. For instance, although the retailer is responsible for selling both new and reconditioned products, the processing cost of these products is considered distinct due to different efforts that need preparation of them.

The total buying cost (*TB*) is characterized as:

$$TB=\sum_{w\in W}\mathscr{Y}_w\left\{P^{'}\sum_{x\in S}\sum_{y\in K}\sum_{t\in T}F_{xytw}+P^{''}\sum_{x\in I}\sum_{y\in M}\sum_{t\in T}R_{xytw}\right\} \tag{12}$$

From Eq. (12), the first term computes the total buying cost of components from suppliers, and the second term indicates the total buying cost of returned products.

The total shortage cost *TS* is described as:

$$TS=\sum_{w\in W}\mathscr{Y}_w\left\{SC\left[\sum_{x\in I}\sum_{t\in T}\theta'_{xtw}+\sum_{x\in I}\sum_{t\in T}\theta''_{xtw}+\sum_{x\in I}\sum_{t\in T}\vartheta_{xtw}\right]\right\} \tag{13}$$

According to Eq. (13), the two first terms compute the shortage cost of new and reconditioned products, respectively. Plus, the last term determines the discarded returns cost in collection centers.

The total holding cost (*TS*) is given as:

$$TH=\sum_{w\in W}\mathscr{Y}_w\left\{HC\left[\frac{\sum_{x\in J}\sum_{t\in T}I_{xtw}}{|T|}\right]\right\} \tag{14}$$

According to Eq. (14), the total holding cost is calculated through the average inventory level in all periods.

The total advertising cost *TA* is declared as:

$$TA=\sum_{w\in W}\mathscr{Y}_w\left\{Ad^*\times\tau\times a\sum_{x\in L}\sum_{y\in I}\sum_{t\in T}R_{xytw}\right\} \tag{15}$$

From Eq. (15), the total advertising cost of reconditioned products is derived from the optimal level of advertising, which is calculated in the first stage. This optimal level breaks down for a unit of the reconditioned product by a given coefficient.

The total reward *TR* is declared as:

$$TR=\sum_{w\in W}\mathscr{Y}_w\left\{RC\left[\frac{\sum_{x\in P}\sum_{y\in Q}\sum_{t\in T}R_{xytw}}{\sum_{x\in Q}\sum_{t\in T}D_{xtw}}-\mathrm{Y}\right]\right\} \tag{16}$$

Eq. (16) represents the total reward by which disassembly canters encourage to efficiently disassemble the returned products to suitable components for selling to customers. In other words, disassembly centers face a loss if they could not prepare the component demands of customers.

The total greening cost *TG* is presented as:

$$TG=\sum_{w\in W}\mathscr{Y}_w\left\{G^*\times\tau'\times c\sum_{x\in K}\sum_{y\in J}\sum_{t\in T}F_{xytw}\right\} \tag{17}$$

Eq. (17) reformulates the total greening cost by taking the first step into account at its optimal level. Similar to advertising level, the optimal greening level is broken down for a unit of product using a proper coefficient.

As a whole, the economic objective Z1 must be maximized as follows:

$$MaxZ1=[TINC-TF-TT-TP-TB-TS-TH-TA-TG+TR] \tag{18}$$

Afterward, the environmental objective should be developed to restrict the emissions of establishing entities and transporting vehicles. Thus, the most polluting entities, including manufacturing centers, reconditioning centers, and disassembly centers, should be limited as possible. Also, the entire transportation should be minimized to reduce CO_2 emissions of truck-load vehicles. Eqs. (19) and (20) respectively declare both aims.

The total fixed emissions *TE* is computed as:

$$TE = \sum_{x\in\{K\cup E\cup P\}}\sum_{t\in T} FE_x Z_{xt} \tag{19}$$

Eq. (19) measures the total emissions of establishing manufacturing centers, reconditioned centers, and disassembly centers.

The total transportation emissions *TTE* is calculated as:

$$TTE = \sum_{w\in W}\mathscr{Y}_w \times \mathrm{TE}\left\{\left[\sum_{x,y\in\mathscr{Z}}\sum_{t\in T} DIS_{xy}F_{xytw}\right] + \left[\sum_{x,y\in\mathscr{U}}\sum_{t\in T} DIS_{xy}R_{xytw}\right]\right\} \tag{20}$$

Eq. (20) determines the total emissions of transporting based on truck-load conditions.

As a group, the environmental objective Z2 must be minimized as follows:

$$MinZ2 = [TE + TTE] \tag{21}$$

Furthermore, the constraints of this model are categorized into five classes, including establishing, capacity, balancing, non-negativity, and binary limitations as follows:

4.2.1. Establishing constraints

$$\sum_{t\in T} Z_{xt} \le 1 \forall x \in \mathscr{F} \tag{22}$$

$$1 \le \sum_{x\in\mathscr{F}}\sum_{t\in T} Z_{xt} \le B \tag{23}$$

Constraints (22) assure that each entity can be established once. Plus, Constraints (23) guarantee that the total number of established entities should be between one entity as a lower bound and a given number (*B*) as a feasible upper bound for all periods.

4.2.2. Capacity constraints

$$\delta\sum_{x\in\mathscr{Z}} F_{xytw} \le \sum_{t'=1}^{t} Z_{yt'} \times CAP_y \forall t \in T; y \in \mathscr{Z}; w \in W \tag{24}$$

$$\delta'\sum_{x\in\mathscr{U}} R_{xytw} \le \sum_{t'=1}^{t} Z_{yt'} \times CAP_y \forall t \in T; y \in \mathscr{U}; w \in W \tag{25}$$

Constraints (24) and (25) ensure that the products' and components' flows from each entity never violate its capacity if that entity has been opened.

4.2.3. Balanced constraints

$$\sum_{x\in L} F_{xytw} + \theta'_{ytw} = D_{ytw} \forall t \in T; y \in I; w \in W \tag{26}$$

$$\sum_{x\in L} R_{xytw} + \theta''_{ytw} = D'_{ytw} \forall t \in T; y \in I; w \in W \tag{27}$$

$$\sum_{y\in M} R_{xytw} + \vartheta_{xtw} = \sigma \times \left(\left[D'_{ytw} - \theta''_{ytw}\right] + \left[D_{ytw} - \theta'_{ytw}\right]\right) \forall t \in T; x \in I; w \in W \tag{28}$$

$$\sum_{x\in K} F_{xytw} + I_{ytw} \ge \sum_{x\in L} F_{yxtw} \forall t \in T; y \in J; w \in W \tag{29}$$

$$I_{xtw} = I_{x,t-1,w} + \sum_{y\in K} F_{yxtw} - \sum_{y\in L} F_{xytw} \forall t \in T; x \in J; w \in W \tag{30}$$

$$\sum_{x\in S} F_{xytw} + \sum_{x\in P} R_{xytw} = \zeta\sum_{x\in J} F_{yxtw} \forall t \in T; y \in K; w \in W \tag{31}$$

$$\sum_{x\in J} F_{xytw} + \sum_{x\in N} R_{xytw} = \sum_{x\in I} F_{yxtw} + \sum_{x\in I} F_{yxtw} \forall t \in T; y \in L; w \in W \tag{32}$$

$$\sum_{x\in I} R_{xytw} = \sum_{x\in N} R_{yxtw} + \sum_{x\in P} R_{yxtw} \forall t \in T; y \in M; w \in W \tag{33}$$

$$\sum_{y\in N} R_{xytw} = \alpha\sum_{y\in I} R_{yxtw} \forall t \in T; x \in M; w \in W \tag{34}$$

$$\sum_{y\in P} R_{xytw} = (1-\alpha)\sum_{y\in I} R_{yxtw} \forall t \in T; x \in M; w \in W \tag{35}$$

$$\sum_{x\in M} R_{xytw} = \sum_{x\in L} R_{yxtw} \forall t \in T; y \in N; w \in W \tag{36}$$

$$\sum_{x\in M} R_{xytw} \le \zeta'\left[\sum_{x\in Q} R_{yxtw} + \sum_{x\in K} R_{yxtw} + \sum_{x\in D} R_{yxtw}\right] \forall t \in T; y \in P; w \in W \tag{37}$$

$$\beta\sum_{x\in M} R_{xytw} \le \zeta'\sum_{x\in K} R_{yxtw} \forall t \in T; y \in P; w \in W \tag{38}$$

$$\beta'\sum_{x\in M} R_{xytw} \le \zeta'\sum_{x\in Q} R_{yxtw} \forall t \in T; y \in P; w \in W \tag{39}$$

$$(1-\beta-\beta')\sum_{x\in M} R_{xytw} \le \zeta'\sum_{x\in D} R_{yxtw} \forall t \in T; y \in P; w \in W \tag{40}$$

$$\sum_{x\in P} R_{xytw} \le D''_{ytw} \forall t \in T; y \in Q; w \in W \tag{41}$$

Constraints (26) to (28) calculate the met or unmet demands and collected or discarded returns for both selling channels. Constraint (29) affirms that the total flows going to a distribution center is greater than or equal to the total flows leaving from them. Constraint (30) computes the inventory level in distribution centers. Also, Constraints (31) to (40) ensure the uniformity of products and components. Finally, Constraint (41) affirms that the volume of sold components to secondary customers is lower than or equal to all demands.

Furthermore, positive and binary constraints are defined as follows:

$$F_{xytw}, R_{xytw}, \theta'_{xtw}, \theta''_{xtw}, \vartheta_{xtw}, I_{xtw} \ge 0; Z_{xt} \in \{0,1\}$$

5. Solution methods

This section provides the solution methods used to solve the studied problem due to the uncertainty of demands. First, the weighted sum method as a well-known method to convert multi-objective problems to single-objective problems is described in detail. Next, the RO model is presented to cope with the uncertainty of demand in the studied problem. Finally, a Lagrangian relaxation algorithm is developed to deal with large-scale cases. Generally, the efficiency and validation of these methods will be proved by solving different instances in Section 6.

The proposed approach of the solution is precisely represented in the following.

5.1. Multi-objective into single-objective

Today, most of the real-world situations are faced with different crucial objectives in which decision-makers can consider multiple objectives in their problems. These objectives often follow different and conflicting aims. Thus, a multi-objective problem tries to get a solution in which all objectives reach to a feasible and optimal outcome (Varsei and Polyakovskiy, 2017). Recently, these problems have been significantly used in many different fields, including management and healthcare (Diabat et al., 2019).

Up to this time, several solution methods have been presented to solve multi-objective problems. These methods can be categorized into various approaches, such as weighted sum, ε-constraint, fuzzy, and LPmetric (Eskandarpour et al., 2015).

In this study, we employ the weighted sum method to convert the studied problem into a single-objective problem.

The weighted sum method is one of the well-known and most widely methods due to its simplicity in formulating as well as combing with other methods (Yang, 2014). Besides, it has been shown that its running time to solve large-scale instances is more reasonable in comparison to other solution methods (Zhen et al., 2019). In this study, these advantages are pivotal to combine the weighted sum method with the proposed Lagrangian relaxation algorithm to solve large-scale instances.

This method converts all the multi-objective functions into a scalar through the weighted sum. Accordingly, the weighted sum is reformulated for the studied MILP model as follows.

$$MinZ3 = \lambda 1 \times (-Z1) + \lambda 2 \times (Z2) \tag{42}$$

So that:

Constraints (22)–(41)

Where, $\lambda 1$and $\lambda 2$define the weighting values which range from zero to one. Note that the proper scaling of the conflicting objectives is needed so that the ranges of each objective should be comparable. That is why we consider the multiplier 10^{-1} to consistent the results of Z1 with Z2 results. For example, Z1 = 3000 × 10^{-1} = 300 and Z2 = 250; this multiplier is derived by using several numerical examples to make consistent objectives.

5.2. Robust optimization

This work focuses on a variety of demands as one of the most likely and prevalent uncertainties that SCs are dealing with in many situations (Mulvey et al., 1995). These uncertainties are due to various reasons, such as unexpected seasonal, pandemic, and disaster events. Therefore, the noisy and incomplete data are frequent and regular. The RO approach has been accepted as a proper response to these types of uncertainties in which there are no historical data and probability distributions (Diabat et al., 2019). The most widely used RO models have been recommended by Mulvey et al. (1995), Ben-Tal and Nemirovski (2008), and Bertsimas and Sim (2003). Here, a developed RO model by Aghezzaf et al. (2010) is considered to deal with the uncertainty of demands. This model is an extension and Mulvey et al. (1995), which use a maximum regret as a variability factor. It is briefly described as follows:

Let W and $\mathscr{Y}_w$ as the finite set of possible scenarios and their probability of occurrence, respectively. After that, the model can be formulated as:

$$Min \gamma . \max_{w \in W} (\xi_w - \xi_w^*) + \varpi \sum_{w \in W} \mathscr{Y}_w \xi_w$$

$$x \in X$$

Where, ξ_w^* is the optimal value obtained by solving the deterministic model under scenario $w \in W$. Besides, ξ_w is the optimal cost that results from the occurrence of scenario w. Also, γ and ϖ are respectively the weights of variability and expected cost. This means that, if decision-makers prioritize lower variability versus higher expected cost, they should increase the weight of γ and vice versa.

In this study, the demand of customers is considered to be uncertain for both the new and reconditioned products' selling channels. Besides, the main objective is maximizing the total profit. As a result, the robust counterpart of this work is reformulated as:

$$MinZ4 = \gamma . \max_{w \in W} (\xi_w - \xi_w^*) + \varpi \sum_{w \in W} \mathscr{Y}_w \xi_w \tag{43}$$

So that:

Constraints (22)–(41)

The complete equation of ξ_w is presented in Appendix B.

Since Eq. (43) is non-linear, it can be linearized by assuming $ZZ = \max_{w \in W} (\xi_w - \xi_w^*)$ and adding the below constraint:

$$ZZ \geq (\xi_w - \xi_w^*) \forall w \in W \tag{44}$$

Finally, using Constraint (44), the proposed RO model can be defined through a MILP as follows:

$$MinZ4 = \gamma . ZZ + \varpi \sum_{w \in W} \mathscr{Y}_w \xi_w \tag{45}$$

So that:

$$ZZ \geq (\xi_w - \xi_w^*) \forall w \in W$$

Constraints (22)–(41)

5.3. Lagrangian relaxation and subgradient algorithm

The CLSC problem has been known as an NP-hard problem (Soleimani and Kannan, 2015). Thus, this problem considerably relates to the scale of instances. Lagrangian relaxation algorithm is presented to cope with solving complicated real-world situations (Fisher, 2004). This method gives an exact lower bound (for minimization problems) or an exact upper bound (for maximization problems). The difference between lower and upper bounds can also be calculated and recognized as a "gap". This method solves a complicated problem due to rough constraints by using its dual form. Indeed, the Lagrangian relaxation model detects an upper bound for the primal model. Next, it finds a lower bound for the dual model. Finally, it updates these bounds to close each other as possible (Diabat et al., 2019).

According to the relevant literature, such as (Zhen et al, 2019), the constraints of satisfying demand are known as rough constraints and relaxing these constraints significantly reduces the complexity of computational time. Therefore, Constraint (26) is relaxed and due to this relaxation a lower bound can be found within a reasonable CPU time.

Consequently, the Lagrangian dual model $Lag(\mathscr{L})$ combined the weighted sum method is reformulated as:

$$MinLag(\mathscr{L}) = \gamma . ZZ + \varpi \sum_{w \in W} \mathscr{Y}_w \xi_w - \sum_{x \in I} \sum_{t \in T} \sum_{w \in W} \mathscr{L}_{xtw} \left(D_{xtw} - \sum_{y \in L} F^{'}_{yxtw} - \theta'_{xtw} \right) \tag{46}$$

Subject to:

$$ZZ \geq (\xi_w - \xi_w^*) \forall w \in W$$

Constraints (22)–(25)

Constraints (27)–(41)

Where, $\mathscr{L}_{itw}$ determines non-negative Lagrange multipliers.

The optimal outcome of Eq. (46) gives an exact lower bound for the studied problem. Plus, values that violate Constraint (26) are considered as penalty values, which also show the infeasibility amount of the primal model. Regarding upper bounds, there exist two different situations. The former is when the solution of the Lagrangian dual problem in Eq. (46) is feasible to the original problem. In this situation, this solution provides an upper bound as well. The latter is when the solution obtained from solving the Lagrangian problem is infeasible. In this situation, the optimal values of Z_{xt} from the Lagrangian dual problem are set as constants and Eq. (45) is minimized subject to all the constraints. The solution to this model is feasible and is an upper-bound on the original problem. Note that the global optimal solution is a fixed upper bound if the model can be solved exactly through GUROBI solver in a predefined interval of time (here, it is 2 h). The efficiency of the proposed algorithm is evaluated by measuring the gap between the Lagrangian relaxation and the GUROBI results for small- and medium scales and the gap between upper bound and lower bound obtained for large-scale instances.

Besides, to update the Lagrange multipliers ($\mathscr{L}_{itw}$) for each iteration, the model is developed based on the subgradient optimization equation.

The subgradient optimization equation for the studied model is presented as Eq. (47).

Table 3
The optimal decision variables of the initializing phase.

	PN^*	PR^*	Ad^*	G^*
Optimal values	9461.2	7558.6	378	1537

$$SO^{\nu} = \frac{\mathscr{K}(\mathrm{UB}^* - \mathrm{Bound}^{\nu})}{\left\| \sum_{l\in L}\sum_{i\in I}\sum_{t\in T}\sum_{w\in W}\left(D_{itw} - \sum_{l\in L} F^{\nu}_{litw} - \theta^{\nu}_{itw}\right)\right\|^2} \tag{47}$$

Where, Bound^{ν} denotes the best bound until iteration ν, UB^* is also a feasible upper bound, and $\mathscr{K}$ is a parameter. In relation to stop conditions, there exist several methods: (a) the maximum iteration number (b) the gap between two consecutive Lagrange multipliers (c) the value of step-size (d) the gap between upper-bound and lower-bound. It is worth noting that the items (b) to (d) confirm that the value of the lower-bound has not changed for a given consecutive iteration number. Here, the gap between two consecutive Lagrange multipliers and the maximum number of iterations are considered as stop conditions, respectively. The pseudo-code of Lagrangian relaxation and subgradient algorithm is represented in Appendix C.

6. Computational results

This section devotes to presenting numerical examples to show the validation and effectiveness of the proposed models and solution methods. Accordingly, in the initializing phase, the coordination model is coded using MATLAB R2012a; the optimal results of the first phase are considered as input parameters for the network design model of the second phase. Thus, the MILP model and solution approaches are coded through GAMS 24.1.2 and solved by the GUROBI solver. These software packages are run by a Personal Computer with Core i5 processor and 4 GB of RAM. It should be noted that the data used in the problem are entirely generated based on the uniform distribution function considering reasonable intervals; these data are presented in Table D1 (Refer to Appendix D).

Now, Table 3 illustrates the results of the initializing phase as follows:

The optimal prices of the new and reconditioned products and the optimal levels of advertising and greening decisions are shown in Table 3. The price of the reconditioned product is determined by 79.89% of the new one price from the above results. This is going to attract and encourage customers to buy a reconditioned product. However, the new product price is also defined at the optimal level for keeping its competitiveness regarding its better advantages such as quality and warranty conditions. Note that the price of buying the returned product is considered as a related variable to the selling price of a new product. Indeed, its optimal value is derived based on a predetermined percentage of the price of the new product. This percentage rate is defined as a uniformly random rate between 10% and 12% in this study. Besides, two other variables i.e., advertising and greening, are set at the optimal values to satisfy both SC profitability and competitive price goals. Due to advertising policy, the reconditioned products gain a more significant market share rather than this policy is ignored. In particular, the supply chain attracts more demands via the reconditioned channel and then experiences more profitability. Along the same vein, greening policy targets profitability by attracting more demands. Indeed, this policy causes demands to increase not only for the new channel but also for the reconditioned channel. So, these two enabling factors simultaneously lead to competitive pricing and profitability. It is noteworthy, the optimal values of greening and advertising show a desirable level for all of the products, and when inserting these values into the second phase, adequate coefficients will be defined in the MILP modeling.

Now, the second phase can be run by using the results of the initializing phase. Thus, the numerical examples in different scales are generated to examine the model and solution methods. In order to simplify, the potential size of each instance is defining as follows: $(|S|, |K|, |J|, |L|, |I|, |M|, |N|, |P|, |Q|, |D|, |T|)$; e.g. (1–2-2–3-5–2-3–2-4–1-6) demonstrates one potential supplier center, two potential manufacturing centers, two potential distribution centers, three potential retail centers, five customers' areas, two potential collection centers, three potential reconditioned centers, two potential recycling centers, four secondary customers' areas, one potential disposal center, and six periods, respectively.

First, the problem is solved using small- and medium-scale instances. The results are shown in Table 4.

According to Table 4, The GUROBI solver can optimally solve the RO model in a few running time. This solver finds the global optimization for all of the instances. On the other hand, the proposed Lagrangian relaxation algorithm also efficiently reaches the exact upper bound. According to the stop condition of the algorithm, the average number of

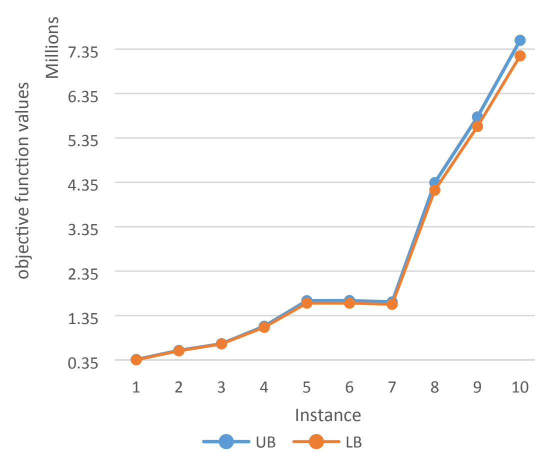

Fig. 3. The gap between UB (Lagrangian) and LB (GUROBI) results.

Table 4
The computation results of the second phase for small- and medium-scales.

Instance	Size	Number of scenarios	GUROBI LB	Lag. UB	Lag. ITER	$\left\|\frac{UB-LB}{UB}\right\| \times 100$	GUROBI time (s)	Lag. Time (s)
1	1–2-3–4-3–2-2–2-3–1-2	3	355,816	359,027	35	0.894	0.480	4.777
2	1–4-5–5-4–2-3–3-5–2-3	3	556,817	564,140	31	1.298	0.500	6.986
3	3–5-7–7-4–3-2–2-6–2-4	3	714,585	714,585	34	0.970	0.552	8.588
4	4–5-8–9-8–5-2–2-7–2-6	3	1,085,870	1,108,740	32	2.060	0.894	14.766
5	5–8-8–10-12–8-5–4-9–4-6	5	1,631,050	1,683,680	30	3.126	1.646	27.624
6	8–10-12–12-15–9-8–6-11–5-6	6	1,629,840	1,686,540	32	3.362	1.896	46.690
7	10–12-13–15-17–12-11–8-12–8-6	6	1,603,580	1,655,670	30	3.146	5.618	64.012
8	10–12-15–15-20–12-12–10-12–9-9	10	4,174,630	4,343,390	27	3.885	15.498	225.834
9	10–15-18–20-25–15-14–12-20–12-12	10	5,608,150	5,822,920	28	3.688	44.491	502.022
10	15–19-18–22-30–23-18–15-24–12-12	15	7,199,350	7,547,830	21	4.617	122.182	622.382
Average					**30**	**2.705**		

Note: The optimal objective functions values converted to positive values by multiplier "-1" (Min(z3) = Max(-z3)).

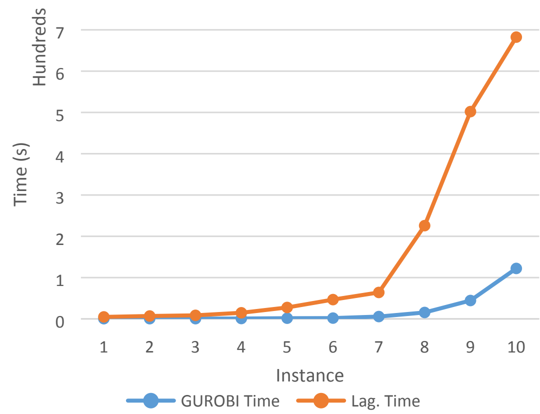

Fig. 4. The gap between the Lagrangian time and the GUROBI time for small- and medium scales.

iteration for the above instances is derived 30.

In order to compare the results and corroborate the applicability of the Lagrangian relaxation algorithm, two aspects are considered. The former is the gap between upper bounds derived by Lagrangian relaxation and lower bounds derived by the GUROBI. The latter is the running time. In this regard, the bound's gap between the Lagrangian upper bound and GUROBI lower bound is only 2.705% on average, which confirms the effectiveness of this algorithm. On the other hand, the running time of GUROBI is less than the Lagrangian relaxation running time. The more iterations of Lagrangian relaxation have been led to increasing the running time compared to the GUROBI solver. However, the Lagrangian relaxation algorithm shows its capability for large-scale instances while provides an exact upper bound within a short CPU time.

Fig. 3 depicts the gap between the optimal result of the GUROBI and the optimal bound of the Lagrangian relaxation algorithm.

Fig. 3 shows the gap between the lower bound, which also shows the global optimal result by the GUROBI solver, and the upper bound, which is calculated by the Lagrangian relaxation algorithm, is satisfactory in all of the instances. Therefore, when the GUROBI solver cannot find a global optimal solution, the results of the proposed algorithm will be acceptable for large instances.

Besides, the running time of both methods is demonstrated in Fig. 4 as:

As shown in Fig. 4, the running time of the Lagrangian relaxation is higher than that of the GUROBI solver. However, the algorithm shows its efficiency for large-scale problems where relaxing the rough constraint of the new product's demand reduces the complexity of the running time. However, in small- and medium-scales, it is rational to use the GUROBI solver to reach both the exact global optimal and a few running time.

Next, the Lagrangian relaxation algorithm's application is checked for the large-scale instances when the exact GUROBI solver is unable to find a global optimal solution within 7200 s (equal to 2 h). This acceptable threshold is defined to evaluate the effectiveness of solution

Table 5
The computation results of the second phase for the large-scale.

Instance	Size	Number of scenarios	GUROBI LB	Lag. LB	Lag. UB	$\left\lvert\frac{UB-LB}{UB}\right\rvert \times 100$	GUROBI time (s)	Lag. Time (s)
1	21–23-25–33-50–21-29–28-29–22-12	20	NA	7,625,640	8,137,219	6.287	>7200	2252.237
2	18–23-25–35-40–30-31–28-35–20-12	25	NA	11,080,103	11,555,384	4.113	>7200	3747.024
3	18–23-22–30-40–30-31–25-35–18-12	30	NA	13,250,133	13,909,399	4.749	>7200	4560.693
4	11–15-17–20-30–17-18–19-21–10-9	35	NA	12,341,900	12,971,700	4.855	>7200	4533.49
5	11–15-19–35-45–17-18–19-35–110-12	40	NA	18,177,959	19,025,815	4.456	>7200	4661.400
6	13–15-14–38-46–22-24–15-30–13-12	45	NA	20,246,830	21,134,210	4.199	>7200	5577.417

Notes: "NA" means the GUROBI solver could not solve the problem and reach the optimal solution within 2 h. The objective functions values converted to positive values by multiplier"-1" (Min(z3) = Max(-z3)).

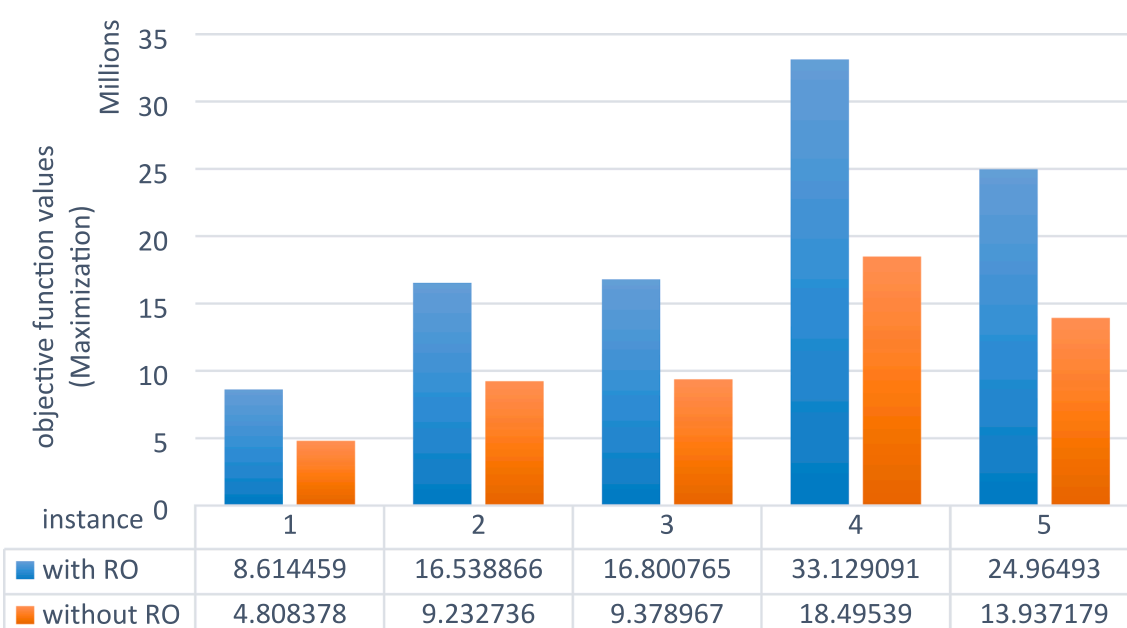

Fig. 5. The comparison of results with RO model and without RO model.

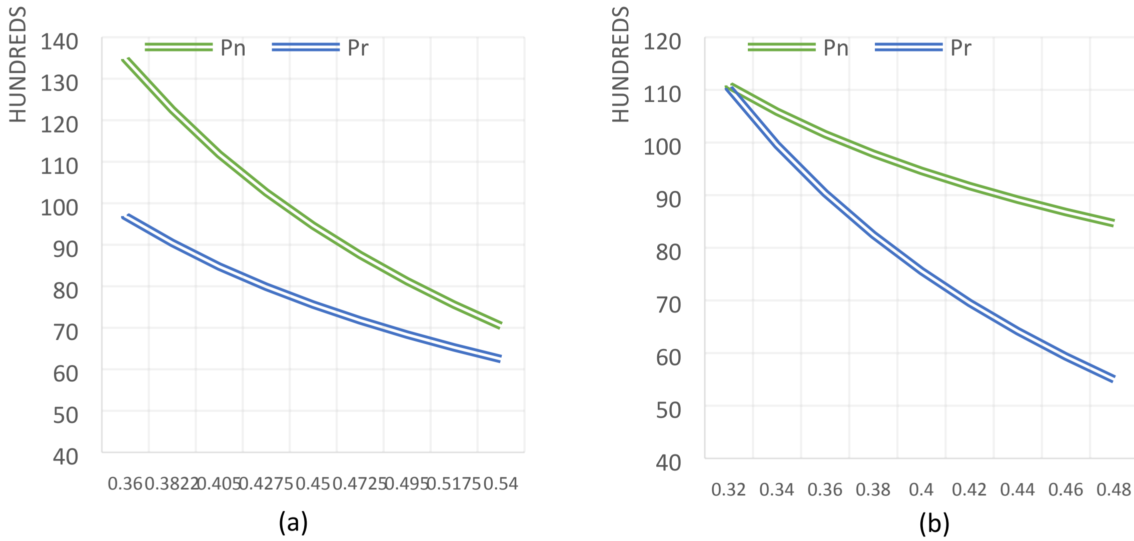

Fig. 6. (a) The effect of new product price elasticity and (b) reconditioned product price elasticity on the price of the new and reconditioned products.

methods in a truncated manner.

Table 5 shows the results of large-scale instances as follows:

According to Table 5, the proposed Lagrangian relaxation algorithm shows its good effectiveness when the scale of instances gets larger, and the GUROBI cannot even reach to a feasible solution in 7200 s. The average bound's gap between the exact upper bound and updated lower bound of the Lagrangian relaxation is less than 5%. Indeed, the Lagrangian algorithm enable to update bounds by repairing $\text{Penalty}(x')$ for the primal model. This bound is very satisfying and acceptable regarding the scale of instances and the gap results.

Finally, to show the effectiveness of the proposed RO model, five numerically instances are solved with the proposed RO model, and without considering this model. The scale and parameters for each instance are equal. Fig. 5 illustrates the difference of results as follows.

According to Fig. 5, the proposed RO model shows a considerable improvement in the final results based on the uncertainty of demands; in fact, the robust optimization makes flexible the SC network in dealing with the uncertain demands of the new and reconditioned products as well as the secondary demands of the components. For example, in instance 3, the final result is improved 1.79 times when the RO model is used versus when the problem is run without the RO model.

As a whole, both phases indicate the effectiveness of the proposed mathematical models and the proposed solution methods. In the first phase, as the initializing phase, the price of the new product not only can maintain its competitiveness, but it also has a reasonable difference with the reconditioned product. This leads to the reconditioned product's price can encourage the customers to order it. As well, the advertising level for the reconditioned product is also a proper enabler to significantly attract its potential demand. Plus, the greening level is set at an optimal level for all the products. This optimal level guarantees both increased demands and the competitiveness of prices. The coordination decisions, in the first phase, ensure that the MILP modeling of the second stage is structured based on the best parameters of pricing, greening, and advertising.

Furthermore, in the second phase, the GUROBI solver solves the small- and medium-scale instances within an intangible time. However, the Lagrangian relaxation also finds an exact bound with a small gap; this gap ensures that results of large-scale instances are acceptable and can be used in real-world situations. On the other hand, the proposed RO model adequately copes with the uncertainty of demands in all of the selling channels and optimally satisfies the economic and environmental objectives.

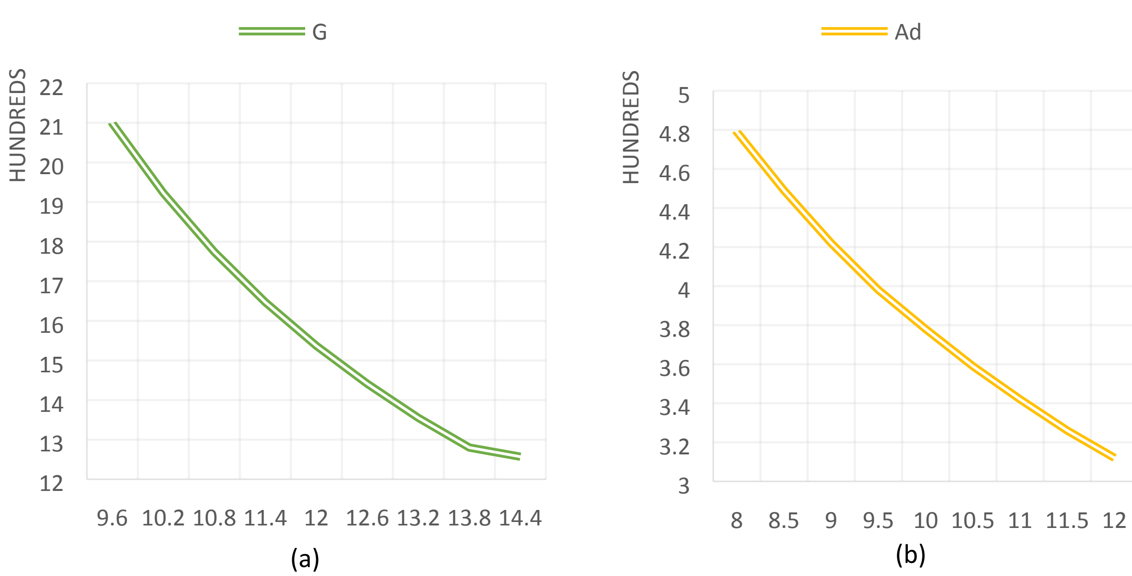

Fig. 7. (a) The effects of cross-price sensitivity on the greening level and (b) advertising elasticity on the advertising level.

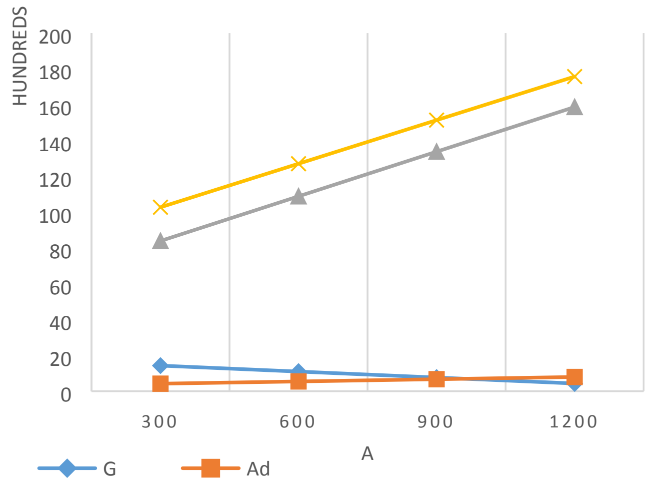

Fig. 8. The role of customers' maximum tolerance in the coordination decisions.

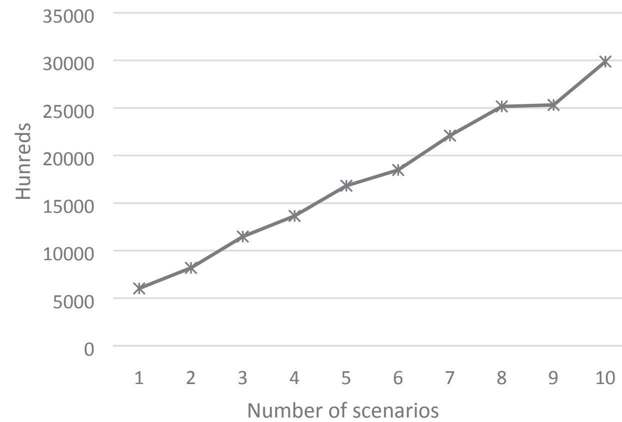

Fig. 9. The number of scenarios versus the optimal objective function.

7. Sensitivity analyses and remarks

This section tries to offer a better understanding of the effects of a number of decisive parameters, and to provide applied directions for the practitioners in real-world situations. The analyses and insights are presented for both stages.

The price of new and reconditioned products has a critical relationship with the price elasticity in both selling channels. Fig. 6 presents these effects for the price of the new and reconditioned products, respectively.

According to Fig. 6(a), the pricing in both channels has a reverse relationship with the rate of the price elasticity of the new product. The results show that when the elasticity rate increases, the difference between prices in both selling channels decreases significantly. Therefore, the decision-makers can considerably reduce the prices of both selling channels to increase their competitiveness, while advancing the profitability of the SC. In other words, by reducing the new product's price, the price of the reconditioned product decreases with a lower rate.

Furthermore, as shown in Fig. 6(b), in contrast to the price elasticity of the new product, by increasing the elasticity rate of the reconditioned product, the gap between the prices of the new and reconditioned products dramatically rises as well. In other words, the decision-makers can use the enhanced rate to propel the demand to buy the reconditioned product and improve the profitability of the SC.

Fig. 7 depicts the effects of the cross-price sensitivity on the optimal greening and advertising levels. It should be noted that cross-price sensitivity is considered to be the same for both selling channels in this study.

Based on Fig. 7(a), the cross-price sensitivity and greening level have an indirect relationship; thus, if the rate of cross-price rises, the decision-makers can obtain the desirable and optimal decision by decreasing investment in greening strategies. This means that the targeted revenue is satisfied; however, the related costs of green quality and technology are reduced. It is noteworthy that the price of the new and reconditioned products, in this state, should be raised to compensate for the reduction in demands caused by decreasing the greening level.

As illustrated in Fig. 7(b), advertising elasticity has a reverse relationship with its optimal level; therefore, as the customers' demand is affected by the advertising, the decision-makers can diminish investing in its strategies. This response strictly depends on different related factors, such as the type of the products an SC provides and the consumption behaviors. However, a lower advertising level is feasible with a higher advertising elasticity.

As mentioned earlier, *"A"* determines the maximum tolerance when the greening level is zero. In addition, this threshold significantly impacts the volume of the returned products. Fig. 8 depicts the effects of variations in this tolerance level.

According to Fig. 8, the customers' maximum tolerance has a direct relationship with the optimal values for the prices of the new and reconditioned products, as well as the optimal advertising level. In contrast, by increasing the threshold, the optimal level of greening reduces. This means that considering the modeling of the initial phase, the network finds an optimal level of greening in a way that the difference in the customers' tolerance and greening levels results in minimizing the cost of the returned products and the cost of greening, while maximizing the total profit of the whole chain. Moreover, the change in pricing is roughly similar for both selling channels, and it has a positive correlation with the customers' maximum tolerance.

The number of scenarios also plays a critical role in the proposed RO model. Fig. 9 traces the effects of the number of scenarios on the optimal value of the robust objective function.

As shown in Fig. 9, the optimal value of the robust objective function increases while the number of scenarios is increasing. Accordingly, the proposed RO model is an efficient response to a large number of existing scenarios. Certainly, SC networks deal with many possible scenarios for customer demand; hence, this proposed model can be realized as an applied modeling and solution method to maximize the desirable objectives under uncertain conditions.

The tradeoffs between the economic and environmental objectives and the Pareto frontier are depicted in Fig. 10.

As can be seen from Fig. 10, the Pareto frontier is computed based on a range of λ from zero to one with a step size of 0.025. While the Pareto results include the negative values of the economic objective, in real-world situations, profitability is still the primary objective, and decision-makers should select profitable decisions among all of the non-dominated solutions. As shown above, the SC network deals with a significant loss until $\lambda = 0.75$, where the environmental objective has its best possible value. Thus, the solution must also be non-dominated; it must also result in an applicable and profitable SC network for real-world situations.

The outputs give several insights for managers in terms of performing coordination and making network design decisions at the same time. Doing so will not only help them maintain their competitive advantages, but it will also assist them in making better decisions in the future.

In summary, the managerial insights can be highlighted as follows:

- Profitability still plays the leading role in prioritizing the applied solutions. Indeed, other factors will lose their significance if the network does not have economic efficiency.
- The RO model reinforces the studied network in dealing with the increasing number of the possible scenarios.
- Cross-price sensitivity directly impacts the greening level in the studied network. Indeed, increasing the cross-price can lead to

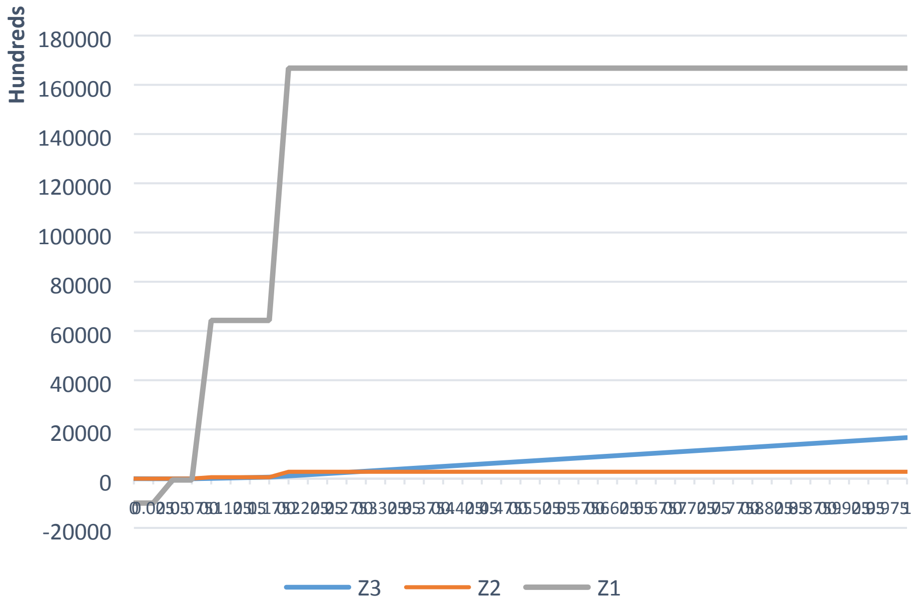

Fig. 10. The trade-off between both objective functions and the Pareto frontier presentation.

savings in the investment in green quality and technology. Equally, advertising elasticity has a direct relationship with its optimal level.

- The customer's maximum tolerance is an important function in defining the optimal value of greening to ensure a desirable revenue for the entire chain.

8. Conclusions and future studies

This study presented a new hybrid approach to simultaneously account for pricing, greening, and advertising decisions and network design objectives. To formulate the demand function, not only pricing impacted customer demand, but also greenness and advertisement had pivotal roles. The coordination structure was developed in terms of the centralized scheme. Using a numerical example, the effectiveness of the models was confirmed. The results showed that the price of the reconditioned products was set at 80% of the price of the new products, which considerably increased the interests of the customers in buying those products. The price of new products kept its competitiveness as well. Moreover, the optimal levels of advertising and greening decisions guaranteed the profitability of the entire chain. The advertising policy led to an increase in the demand for the reconditioned products. The greening policy led to an increase in the entire demands of both new and reconditioned channels. The MILP model was formulated based on the best coordination results, and then it was run for several examples at different scales. Since various possible scenarios were considered, the MILP model was developed based on the RO. The obtained results confirmed that the proposed RO model significantly improved the outputs, i.e., >1.5 times compared to the case where no robust approach was used. Moreover, the results of the Lagrangian relaxation algorithm indicated that large-scale instances could be solved in polynomial time. This algorithm shows only a 2.7% deviation from the global optimal results. Based on the managerial insights, the economic objective played the main role in designing the network.

Although this paper presents some interesting managerial insights, it faces a number of limitations. The paper considers a linear price-dependent demand. Therefore, other types of demand functions can be modeled as well. Furthermore, the network can be studied in terms of decentralized and transitional structures. In addition, we assumed that the customer's demand is uncertain, while the other parameters were considered static.

Future studies can focus on developing other supply chain configurations. Moreover, some assumptions, such as capacitated vehicles, can be developed. Researchers can also study the decomposition solution methods, such as Benders decomposition and branch and price, to compare their results with the findings of this study.

CRediT authorship contribution statement

Behrooz Khorshidvand: Conceptualization, Methodology, Software, Validation, Writing - review & editing. **Hamed Soleimani:** Conceptualization, Methodology, Software, Validation, Supervision. **Soheil Sibdari:** Conceptualization, Methodology. **Mir Mehdi Seyyed Esfahani:** Conceptualization, Formal analysis.

Appendix A

As before mentioned, the studied SC is organized on the centralized basis; thus, the Hessian matrix of Eq. (3) is checked for the concavity condition.

$$H = \begin{bmatrix} -2k_n & 2k_c & v\times delta\times(k_c-k_n) & 0 \\ 2k_c & -2k_r & v\times delta\times(k_c-k_r) & k_a \\ v\times delta\times(k_c-k_n) & v\times delta\times(k_c-k_r) & -c & 0 \\ 0 & k_a & 0 & -a \end{bmatrix} \tag{A1}$$

Matrix H can be considered concave if its determinant shows positive value for even scales and negative value for odd scales. Therefore, the results are given as follows:

$|H_{1\times1}| = -2k_n < 0$

$$|H_{2\times2}| = 4k_c k_r - 4k_c^2 > 0$$

$$|H_{3\times3}| = -2k_n \times \left(2k_r \times c - (v \times delta \times (k_c - k_r))^2\right) \langle 0$$

$$|H_{4\times4}| = -2k_n \times \left(-2k_r \times c \times a + a \times (v \times delta \times (k_c - k_r))^2 + k_a^2 \times c\right) \rangle 0$$

According to the above results, the concavity of matrix H is proved; thus, the first order optimally conditions for Eq. (3) can be obtained as:

$$\frac{\partial \Pi_T}{\partial PN} = 0 \quad 2k_c \times PR - 2k_n \times PN - (\ell - 1) \times E(\rho) - v \times (k_c - k_n) \times (A - G \times delta) = 0 \tag{A2}$$

$$\frac{\partial \Pi_T}{\partial PR} = 0 \quad 2k_c \times PN - 2k_r \times PR + k_a \times Ad - \ell \times E(\rho) - v \times (k_c - k_r) \times (A - G \times delta) = 0 \tag{A3}$$

$$\frac{\partial \Pi_T}{\partial G} = 0 \quad v \times delta \times (E(\rho) + PN \times (k_c - k_n) + PR \times (k_c - k_r)) - G \times c = 0 \tag{A4}$$

$$\frac{\partial \Pi_T}{\partial Ad} = 0 \quad k_a \times PR - Ad \times a = 0 \tag{A5}$$

From Eqs. (A2)–(A5), the optimal values of pricing, greening, and advertising are calculated as follows:

$$PN^* = {x_6}^{-1} \times \left[\frac{2k_c}{x_5} \times (\ell \times E(\rho) - v \times x_3 \times (A - x_4 \times E(\rho))) - (1 - \ell) \times E(\rho) - v \times x_2 \times \left(A - x_4 \times \left(E(\rho) + \frac{x_3}{x_5} \times (\ell \times E(\rho) - v \times x_3 \times (A - x_4 \times E(\rho)))\right)\right)\right] \tag{A6}$$

$$PR^* = {x_5}^{-1} \times [\ell \times E(\rho) + 2k_c \times PN^* - v \times x_3 \times (A - x_4 \times (E(\rho) + PN^* \times x_2))] \tag{A7}$$

$$G^* = \frac{x_4}{delta} \times [E(\rho) + PN^* \times x_2 + PR^* \times x_3] \tag{A8}$$

$$Ad^* = [PR^* \times x_1] \tag{A9}$$

Where,

$$x_1 = k_a \times a^{-1}$$

$$x_2 = k_c - k_n$$

$$x_3 = k_c - k_r$$

$$x_4 = delta^2 \times v \times c^{-1}$$

$$x_5 = 2k_r - k_a \times x_1 - v \times x_3^2 \times x_4$$

$$x_6 = 2k_n - x_5^{-1} \times (4k_c \times v \times x_2 \times x_3 \times x_4) - v \times x_4 \times x_2^2 - x_5^{-1} \times \left(v \times x_2 \times x_3^2 \times x_4^2\right) - 4k_c^2 \times x_5^{-1}$$

Consequently, Theorem 1 is approved.■

Appendix B

The cost function of ξ_w is calculated as follows:

$$\begin{aligned}\xi_w = \lambda 1 \Bigg(& - \left\{ PN^* \sum_{x\in L}\sum_{y\in I}\sum_{t\in T} F_{xytw} + PR^* \sum_{x\in L}\sum_{y\in I}\sum_{t\in T} F_{xytw} + PCO \sum_{x\in P}\sum_{y\in Q}\sum_{t\in T} R_{xytw} \right\} + \left\{ \sum_{x\in \mathscr{F}}\sum_{t\in T} FC_x Z_{xt} \right\} + \Bigg\{ TC \Bigg[\sum_{x,y\in \mathscr{Z}}\sum_{t\in T} DIS_{xy} F_{xytw} \\ & + \sum_{x,y\in \mathscr{U}}\sum_{t\in T} DIS_{xy} R_{xytw} \Bigg] \Bigg\} + \left\{ \sum_{x,y\in \mathscr{Z}}\sum_{t\in T} PC_x F_{xytw} + \sum_{x,y\in \mathscr{U}}\sum_{t\in T} PC_x R_{xytw} \right\} + \left\{ P' \sum_{x\in S}\sum_{y\in K}\sum_{t\in T} F_{xytw} + P'' \sum_{x\in I}\sum_{y\in M}\sum_{t\in T} R_{xytw} \right\} + \Bigg\{ SC \Bigg[\sum_{x\in I}\sum_{t\in T} \theta'_{xtw} + \sum_{x\in I}\sum_{t\in T} \theta''_{xtw} \\ & + \sum_{x\in I}\sum_{t\in T} \vartheta_{xtw} \Bigg] \Bigg\} + \left\{ HC \left[\frac{\sum_{x\in J}\sum_{t\in T} I_{xtw}}{|T|} \right] \right\} + \left\{ Ad^* \times \tau \times a \sum_{x\in K}\sum_{y\in J}\sum_{t\in T} F_{xytw} \right\} - \left\{ RC \left[\frac{\sum_{x\in P}\sum_{y\in Q}\sum_{t\in T} R_{xytw}}{\sum_{x\in Q}\sum_{t\in T} D_{xtw}} - \mathrm{Y} \right] \right\} + \Bigg\{ G^* \times \tau' \\ & \times c \sum_{x\in K}\sum_{y\in J}\sum_{t\in T} F_{xytw} \Bigg\} \Bigg) + \lambda 2 \left(\left\{ \sum_{x\in\{K\cup E\cup P\}}\sum_{t\in T} FE_x Z_{xt} \right\} + \left\{ TE \left[\sum_{x,y\in \mathscr{Z}}\sum_{t\in T} DIS_{xy} F_{xytw} + \sum_{x,y\in \mathscr{U}}\sum_{t\in T} DIS_{xy} R_{xytw} \right] \right\} \right) \forall w \\ & \in W\end{aligned}$$

Table D1
The dataset.

parameter	uniform random	parameter	uniform random	parameter	uniform random	parameter	uniform random
$DIS_{x\in S,y\in K}$	[50 100]	$PC_{x\in J}$	[3 8]	$CAP_{x\in P}$	[50 200]	τ	[0.1 0.15]
$DIS_{x\in K,y\in J}$	[100 200]	$PC_{x\in L}$	[3 5]	$D'_{x\in I,tw}$	[200 300]	τ'	[0.1 0.15]
$DIS_{x\in J,y\in L}$	[50 100]	$PC_{x\in M}$	[3 5]	$D''_{x\in I,tw}$	[100 200]	Y	[0.3 0.5]
$DIS_{x\in L,y\in I}$	[5 15]	$PC_{x\in E}$	[2 5]	$D_{x\in Q,tw}$	[10 100]	ℓ	[0.6 0.7]
$DIS_{x\in M,y\in E}$	[5 15]	$PC_{x\in P}$	[3 6]	P'	[3000 4000]	c	[8 12]
$DIS_{x\in M,y\in P}$	[50 100]	SC	[200 300]	P''	[0.1 0.12]*PN	k_c	[0.2 0.4]
$DIS_{x\in E,y\in L}$	[10 20]	HC	[10 50]	PCO	P'	k_a	[0.5 1]
$DIS_{x\in P,y\in K}$	[50 80]	AC	[5 10]	δ	[1 1.2]	k_r	[0.2 0.4]
$DIS_{x\in P,y\in Q}$	[5 10]	RC	[10 30]	δ'	[0.3 1]	k_n	[0.45 0.5]
$DIS_{x\in P,y\in D}$	[20 50]	TE	[05 0.8]	ζ	[0.1 0.5]	*delta*	[0.2 0.4]
TC	[1.5 2.5]	$FE_{x\in K}$	[50 100]	ζ'	[1 1.2]	$\lambda 1$	[0.5 0.6]
$FC_{x\in K}$	[500 1000]	$FE_{x\in E}$	[50 100]	$I_{x\in J,0w}$	0	$\lambda 2$	1-λ1
$FC_{x\in J}$	[400 800]	$FE_{x\in P}$	[40 80]	σ	[0.12 0.15]	$E(\rho)$	[5000 10000]
$FC_{x\in L}$	[250 500]	$CAP_{x\in K}$	[500 1000]	ν	$PC_{x\in K}$	γ	[0.3 0.5]
$FC_{x\in M}$	[200 400]	$CAP_{x\in J}$	[300 1000]	α	[0.5 0.7]	ϖ	1-γ
$FC_{x\in E}$	[200 400]	$CAP_{x\in L}$	[500 800]	A	[200 250]		
$FC_{x\in P}$	[250 500]	$CAP_{x\in M}$	[500 700]	β	[0.3 0.4]		
$PC_{x\in K}$	[5 12]	$CAP_{x\in N}$	[100 300]	β'	1-β		

Appendix C

Algorithm 1. (*: Pseudo-code of Lagrangian relaxation and subgradient algorithm*)

{*Phase* 0: *input*}
set a best bound for the primal model: best bound$= -inf$
set a feasible upper bound for the primal model: upper bound$=\mathrm{UB}^*$
set an initial Lagrange multiplier: $\mathscr{L}_{itw}=$ *max* [0, *the dual values of Constraint* (26)]
{*Phase* 1: *Initialization*}
max Iteration $=$ *ITER*. (*Here, it is* 50); $\mathscr{K} = 1$; *Non-improvement* $= 0$;
{*Phase* 2: *Subgradient optimization*}
for $j = 1, 2, \cdots, ITER$;
begin
solve the dual model;
if the optimal value of relaxation model $(\mathrm{Bound}^{j}) >$ *best bound*
then best bound $=\mathrm{Bound}^{j}$;
else if
Non-improvement $\rightarrow$ *Non-improvement* $+ 1$;
if Non-improvement $\geq \mathscr{K}$
then $\mathscr{K} \rightarrow \mathscr{K}/2$ *and Non-improvement* $= 0$;
calculate Step-size (SO^{j}) *and update upper bound;*
$\mathrm{gradient}^{j} = \mathrm{Penalty}(x^{j})$;
update UB *for primal model;*
if $\mathrm{Penalty}\left(x^{j}\right) = 0$
$\mathrm{UB}(x^{j})$;
else if
$\mathrm{UB}\left(x^{j}\right) =$ *Min Eq.* (45) *subject to all constraints, with set*
the optimal values of $Z_{x^{j}}$ *as constants.*
$SO^{j} = \frac{\mathscr{K}(\mathrm{UB} - \mathrm{Bound}^{j})}{\|\mathrm{gradient}^{j}\|^2}$;
$\mathscr{L}_{itw}^{j+1} = \max\left(0, \mathscr{L}_{itw}^{j} + SO^{j} \times \mathrm{gradient}^{j}\right)$;
if $\|\mathscr{L}_{itw}^{j+1} - \mathscr{L}_{itw}^{j}\| <$ *a small number* (*here, it is* 0.001)
end

Appendix D

The dataset used in Sections 5 and 6 is defined in Table D1.

Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2021.107326.

References

Aghezzaf, E. H., Sitompul, C., & Najid, N. M. (2010). Models for robust tactical planning in multi-stage production systems with uncertain demands. *Computers & Operations Research, 37*(5), 880–889.

Agi, M. A., & Yan, X. (2019). Greening Products in a Supply Chain under Market Segmentation and Different Channel Power Structures. *International Journal of Production Economics, 107523*.

Ahi, P., & Searcy, C. (2015). An analysis of metrics used to measure performance in green and sustainable supply chains. *Journal of Cleaner Production, 86*, 360–377.

Ahmed, W., & Sarkar, B. (2018). Impact of carbon emissions in a sustainable supply chain management for a second generation biofuel. *Journal of cleaner production, 186*, 807–820.

Alamdar, S. F., Rabbani, M., & Heydari, J. (2018). Pricing, collection, and effort decisions with coordination contracts in a fuzzy, three-level closed-loop supply chain. *Expert Systems with Applications, 104*, 261–276.

Ansari, Z. N., & Kant, R. (2017). A state-of-art literature review reflecting 15 years of focus on sustainable supply chain management. *Journal of cleaner production, 142*, 2524–2543.

Badi, S., & Murtagh, N. (2019). Green supply chain management in construction: A systematic literature review and future research agenda. *Journal of Cleaner Production, 223*, 312–322.

Bairamzadeh, S., Saidi-Mehrabad, M., & Pishvaee, M. S. (2018). Modelling different types of uncertainty in biofuel supply network design and planning: A robust optimization approach. *Renewable energy, 116*, 500–517.

Ben-Tal, A., & Nemirovski, A. (2008). Selected topics in robust convex optimization. *Mathematical Programming, 112*(1), 125–158.

Bertsimas, D., & Sim, M. (2003). Robust discrete optimization and network flows. *Mathematical programming, 98*(1–3), 49–71.

Diabat, A., Jabbarzadeh, A., & Khosrojerdi, A. (2019). A perishable product supply chain network design problem with reliability and disruption considerations. *International Journal of Production Economics, 212*, 125–138.

Eskandarpour, M., Dejax, P., Miemczyk, J., & Péton, O. (2015). Sustainable supply chain network design: An optimization-oriented review. *Omega, 54*, 11–32.

Farshbaf-Geranmayeh, A., & Zaccour, G. (2020). Pricing and Advertising in a Supply Chain in the Presence of Strategic Consumers. *Omega, 102239*.

Fisher, M. L. (2004). The Lagrangian relaxation method for solving integer programming problems. *Management science, 50*(12_supplement), 1861–1871.

Ghaderi, H., Moini, A., & Pishvaee, M. S. (2018). A multi-objective robust possibilistic programming approach to sustainable switchgrass-based bioethanol supply chain network design. *Journal of cleaner production, 179*, 368–406.

Ghelichi, Z., Saidi-Mehrabad, M., & Pishvaee, M. S. (2018). A stochastic programming approach toward optimal design and planning of an integrated green biodiesel supply chain network under uncertainty: A case study. *Energy, 156*, 661–687.

Giannoccaro, I. (2018). Centralized vs. decentralized supply chains: The importance of decision maker's cognitive ability and resistance to change. *Industrial Marketing Management, 73*, 59–69.

Govindan, K., Mina, H., Esmaeili, A., & Gholami-Zanjani, S. M. (2020). An integrated hybrid approach for circular supplier selection and closed loop supply chain network design under uncertainty. *Journal of Cleaner Production, 242*, Article 118317.

Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. *European Journal of Operational Research, 263*(1), 108–141.

Govindan, K., & Soleimani, H. (2017). A review of reverse logistics and closed-loop supply chains: A Journal of Cleaner Production focus. *Journal of Cleaner Production, 142*, 371–384.

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research, 240*(3), 603–626.

Guide, V. D. R., Jr, & Van Wassenhove, L. N. (2009). OR FORUM—The evolution of closed-loop supply chain research. *Operations research, 57*(1), 10–18.

Haddad-Sisakht, A., & Ryan, S. M. (2018). Closed-loop supply chain network design with multiple transportation modes under stochastic demand and uncertain carbon tax. *International Journal of Production Economics, 195*, 118–131.

Hamdan, B., & Diabat, A. (2020). Robust design of blood supply chains under risk of disruptions using Lagrangian relaxation. *Transportation Research Part E: Logistics and Transportation Review, 134*, Article 101764.

Heidari-Fathian, H., & Pasandideh, S. H. R. (2018). Green-blood supply chain network design: Robust optimization, bounded objective function & Lagrangian relaxation. *Computers & Industrial Engineering, 122*, 95–105.

Heydari, J., Govindan, K., & Aslani, A. (2018). Pricing and greening decisions in a three-tier dual channel supply chain. *International Journal of Production Economics*.

Hickman, R., Ashiru, O., & Banister, D. (2011). Transitions to low carbon transport futures: Strategic conversations from London and Delhi. *Journal of Transport Geography, 19*(6), 1553–1562.

Hong, Z., & Guo, X. (2019). Green product supply chain contracts considering environmental responsibilities. *Omega, 83*, 155–166.

Hu, B., Feng, Y., & Chen, X. (2018). Optimization and coordination of supply chains under the retailer's profit margin constraint. *Computers & Industrial Engineering, 126*, 569–577.

Jahani, H., Abbasi, B., Alavifard, F., & Talluri, S. (2018). Supply chain network redesign with demand and price uncertainty. *International Journal of Production Economics, 205*, 287–312.

Kazemi, N., Modak, N. M., & Govindan, K. (2019). A review of reverse logistics and closed loop supply chain management studies published in IJPR: A bibliometric and content analysis. *International Journal of Production Research, 57*(15–16), 4937–4960.

Krishnan, H., & Winter, R. A. (2011). On the role of revenue-sharing contracts in supply chains. *Operations Research Letters, 39*(1), 28–31.

Liu, P., & Yi, S. P. (2017). Pricing policies of green supply chain considering targeted advertising and product green degree in the big data environment. *Journal of Cleaner Production, 164*, 1614–1622.

Liu, Y., Liu, Z. Y., Ren, W. W., & Forrest, J. Y. L. (2020). A coordination mechanism through relational contract in a two-echelon supply chain. *Journal of Retailing and Consumer Services, 56*, Article 102156.

Ma, H., & Li, X. (2018). Closed-loop supply chain network design for hazardous products with uncertain demands and returns. *Applied Soft Computing, 68*, 889–899.

Mohseni, S., & Pishvaee, M. S. (2016). A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. *Computers & Industrial Engineering, 100*, 58–71.

Mondal, C., & Giri, B. C. (2020). Pricing and used product collection strategies in a two-period closed-loop supply chain under greening level and effort dependent demand. *Journal of Cleaner Production, 121335*.

Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations research, 43*(2), 264–281.

Nayeri, S., Paydar, M. M., Asadi-Gangraj, E., & Emami, S. (2020). Multi-objective Fuzzy Robust Optimization Approach to Sustainable Closed-Loop Supply Chain Network Design. *Computers & Industrial Engineering, 106716*.

Özkır, V., & Başlıgil, H. (2013). Multi-objective optimization of closed-loop supply chains in uncertain environment. *Journal of Cleaner Production, 41*, 114–125.

Parsaeifar, S., Bozorgi-Amiri, A., Naimi-Sadigh, A., & Sangari, M. S. (2019). A game theoretical for coordination of pricing, recycling, and green product decisions in the supply chain. *Journal of Cleaner Production, 226*, 37–49.

Peidro, D., Mula, J., Poler, R., & Lario, F. C. (2009). Quantitative models for supply chain planning under uncertainty: A review. *The International Journal of Advanced Manufacturing Technology, 43*(3–4), 400–420.

Peng, H., Shen, N., Liao, H., Xue, H., & Wang, Q. (2020). Uncertainty factors, methods, and solutions of closed-loop supply chain—A review for current situation and future prospects. *Journal of Cleaner Production, 254*, Article 120032.

Phouratsamay, S. L., & Cheng, T. C. E. (2019). The single-item lot-sizing problem with two production modes, inventory bounds, and periodic carbon emissions capacity. *Operations Research Letters, 47*(5), 339–343.

Pishvaee, M. S., & Khalaf, M. F. (2016). Novel robust fuzzy mathematical programming methods. *Applied Mathematical Modelling, 40*(1), 407–418.

Polo, A., Peña, N., Muñoz, D., Cañón, A., & Escobar, J. W. (2019). Robust design of a closed-loop supply chain under uncertainty conditions integrating financial criteria. *Omega, 88*, 110–132.

Prajapati, H., Kant, R., & Shankar, R. (2019). Bequeath life to death: State-of-art review on reverse logistics. *Journal of cleaner production, 211*, 503–520.

Prakash, S., Kumar, S., Soni, G., Jain, V., & Rathore, A. P. S. (2020). Closed-loop supply chain network design and modelling under risks and demand uncertainty: An integrated robust optimization approach. *Annals of Operations Research, 290*(1), 837–864.

Ranjan, A., & Jha, J. K. (2019). Pricing and coordination strategies of a dual-channel supply chain considering green quality and sales effort. *Journal of Cleaner Production, 218*, 409–424.

Sauer, P. C., & Seuring, S. (2019). Extending the reach of multi-tier sustainable supply chain management–Insights from mineral supply chains. *International Journal of Production Economics, 217*, 31–43.

Shen, J. (2020). An environmental supply chain network under uncertainty. *Physica A: Statistical Mechanics and its Applications, 542*, Article 123478.

Schewe, L., Schmidt, M., & Weninger, D. (2020). A decomposition heuristic for mixed-integer supply chain problems. *Operations Research Letters*.

Sibdari, S., & Pyke, D. F. (2014). Dynamic pricing with uncertain production cost: An alternating-move approach. *European Journal of Operational Research, 236*(1), 218–228.

Soleimani, H., Govindan, K., Saghafi, H., & Jafari, H. (2017). Fuzzy multi-objective sustainable and green closed-loop supply chain network design. *Computers & Industrial Engineering, 109*, 191–203.

Soleimani, H., & Kannan, G. (2015). A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks. *Applied Mathematical Modelling, 39*(14), 3990–4012.

Souza, G. C. (2013). Closed-loop supply chains: A critical review, and future research. *Decision Sciences, 44*(1), 7–38.

Thomas, D. J., & Griffin, P. M. (1996). Coordinated supply chain management. *European journal of operational research, 94*(1), 1–15.

Varsei, M., & Polyakovskiy, S. (2017). Sustainable supply chain network design: A case of the wine industry in Australia. *Omega, 66*, 236–247.

Wang, J., Jiang, H., & Yu, M. (2020). Pricing decisions in a dual-channel green supply chain with product customization. *Journal of Cleaner Production, 247*, Article 119101.

Wang, L., & Song, Q. (2020). Pricing policies for dual-channel supply chain with green investment and sales effort under uncertain demand. *Mathematics and Computers in Simulation, 171*, 79–93.

Wu, J., Jiang, F., & He, Y. (2018). Pricing and horizontal information sharing in a supply chain with capacity constraint. *Operations Research Letters, 46*(4), 402–408.

Xiao, D., Zhou, Y. W., Zhong, Y., & Xie, W. (2019). Optimal cooperative advertising and ordering policies for a two-echelon supply chain. *Computers & Industrial Engineering, 127*, 511–519.

Xie, J., Liang, L., Liu, L., & Ieromonachou, P. (2017). Coordination contracts of dual-channel with cooperation advertising in closed-loop supply chains. *International Journal of Production Economics, 183*, 528–538.

Yang, X. S. (2014). *Nature-inspired optimization algorithms*. Elsevier.

Yu, H., & Solvang, W. D. (2020). A fuzzy-stochastic multi-objective model for sustainable planning of a closed-loop supply chain considering mixed uncertainty and network flexibility. *Journal of Cleaner Production, 121702*.

Zailani, S., Jeyaraman, K., Vengadasan, G., & Premkumar, R. (2012). Sustainable supply chain management (SSCM) in Malaysia: A survey. *International Journal of Production Economics, 140*(1), 330–340.

Zhang, Z., Liu, S., & Niu, B. (2019). Coordination mechanism of dual-channel closed-loop supply chains considering product quality and return. *Journal of Cleaner Production, 119273*.

Zhen, L., Wu, Y., Wang, S., Hu, Y., & Yi, W. (2018). Capacitated closed-loop supply chain network design under uncertainty. *Advanced Engineering Informatics, 38*, 306–315.

Zhen, L., Huang, L., & Wang, W. (2019). Green and sustainable closed-loop supply chain network design under uncertainty. *Journal of Cleaner Production, 227*, 1195–1209.