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OPTIMIZATION

Simulation–optimization approach for the multi-objective production and distribution planning problem in the supply chain: using NSGA-II and Monte Carlo simulation

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Abstract
With the growth of multinational companies, increasing international and domestic competition between companies, upgrading information technology, and increasing customer expectations, accurate supply chain (SC) planning is essential. In such an environment, pollution has become more severe in recent decades, and with the weakening of the environment and global warming, green SC management strategies have become significant issues in recent decades. In this research, we consider the integrated production and distribution planning problem of a multi-level green closed-loop SC system, which includes multiple recycling, manufacturing/ remanufacturing, and distribution centers. We present a three-level bi-objective programming model to maximize profit and minimize the amount of greenhouse gas emissions. A hierarchical iterative approach utilizing the LP-metric method and the non-dominated sorting genetic algorithm (NSGA-II) is introduced to solve the proposed model. The Taguchi approach is applied to find optimum control parameters of NSGA-II. Moreover, Monte Carlo (MC) simulation is applied to tackle uncertainty in demand, and the NSGA-II algorithm is integrated with MC simulation (MCNSGA-II). Through numerical experiments on randomly generated instances, we observe that the average of the relative gaps NSGA-II and LP-metric method are 7%, 7%, and 1% for the three levels, respectively. Furthermore, it is observed that the value of convergence (C) and spacing (S) metrics of the MCNSGA-II algorithm are 0 and 1.82E + 07, which are better than NSGA-II.

Keywords Production and distribution planning · Simulation–optimization · Green closed-loop supply chain · Monte Carlo simulation · Three-level bi-objective programming · NSGA-II algorithm

1 Introduction

Many companies strive to meet their expectations and customer satisfaction to modify and expand their business processes so that they can successfully challenge the growth of competitive environments. Therefore, SC management (SCM) is an attractive topic (Ramezani et al. 2014). An SC contains all activities that convert raw materials into final products and transfer them to customers. Production planning and distribution planning are the two core optimization problems in SCM, which are always linked together (Jing and Li 2018; Kang et al 2016). Production planning includes decisions regarding usual time and overtime production, hiring and firing of labor, machine capacity, and subcontracting are made for a planning horizon. Distribution planning decisions are related to determining which facilities would provide to the demands of which markets (Fahimnia et al. 2013).

In the past, the elements of an SC, such as manufacturers and distributors, have been considered as discrete commerce entities looking for their maximum profits (Barbarosoğlu and Özgür 1999). Nevertheless, this may lead to problems between companies in an SC. Because the benefits of the firms cannot be balanced and maximizing

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profits for individual companies does not mean maximizing profits for the entire SC. Therefore, the overall efficiency and operational performance of the SC depend on integrated PD planning decisions (Liang and Cheng 2009).

In the past few years, topics like green remanufacturing and manufacturing, waste management, and reverse logistics as important subsets of GSCM have received a lot of attention. Note that the integration of environmental consideration into SCM specifies GSCM (Srivastava 2008).

Optimization of fuel consumption, gas emission reduction, and waste management are important in the GCLSC network design problem (Lin et al. 2014). Today, gas emissions are an important environmental issue; thus, transportation has been considered by green logistics researchers (Dekker et al. 2012).

Moreover, product recycling has faced increasing attention throughout the years. Today, more companies employ voluntarily and positively in the products recycling and remanufacturing business by considering economic benefits. Accordingly, the common forward SC is converted into the closed-form through integrating recycling and remanufacturing (Jing and Li 2018).

Consequently, in this study, we investigate the integrated PD planning problem for the GCLSC, which is multi-product, multi-period, and multi-level. In the GCLSC, the multiple recycling centers disassembled the returned products to components. They have been saved in the inventory of eligible components if they have a remanufacturing standard and are carried to various remanufacturing/ manufacturing centers. The remanufacturing/manufacturing centers test the quality and efficiency of eligible components, or raw materials are converted to new components. Remanufactured and new components are used to produce remanufactured and new products, respectively. The products are added to the inventory of remanufactured and new products and are carried to various distribution centers according to orders. Each distribution center can select one or more remanufacturing/manufacturing centers for satisfying demand, and provide remanufactured or new products to retailers for sales. Moreover, the returned products from retailers are gathered and recycled by distribution centers and carried to multiple recycling centers. Note that there are several kinds of vehicles to transport parts and products between the GCLSC components.

There are many decision-makers at different levels of the GCLSC that have various decision-making authorities and objectives. The set of strategies and the goal attainment of lower levels can be affected by the decisions from the upper levels. Nevertheless, lower levels have considerable autonomy, so the upper levels cannot control them. Generally, each level of the SC is finding the best decision considering the decisions of the other levels. Therefore, multi-level modeling of the problem is considered with the aim to maximize profit and minimize adverse environmental impacts at each level.

There are many questions about the considered GCLSC, e.g., amount of returned products that are disassembled and tested in recycling centers, amount of components that are disposed of in recycling centers, inventory quantity of returned products at recycling centers, amount of remanufactured products that are assembled in factories, inventory quantity of remanufactured products in factories, amount of returned products that are collected by distributors from downstream markets. Therefore, to answer the questions and other ones, we present a multi-level bi-objective programming model that includes multiple recycling, manufacturing/remanufacturing factories, and distribution centers. A hierarchical iterative approach using the LP-metric method for small-size instances and the NSGA-II algorithm for large-size instances is suggested to solve the proposed model. There are some metaheuristic algorithms such as multi-objective gray wolf optimizer (MOGWO) (Mirjalili et al. 2016), multi-objective water cycle algorithm (MOWCA) (Sadollah et al. 2015), multi-objective particle swarm optimization (MOPSO) (Kumar and Minz 2014) and multi-objective gravitational search algorithm (MOGSA) (Hassanzadeh and Rouhani 2010) to solve multi-objective optimization problems. The NSGA-II algorithm is a sub-type of the genetic algorithm (GA) used for solving multi-objective optimization problems. It is one of the most efficient multi-objective evolutionary algorithms Kheiri (2018). Moreover, Verma et al. (2021) provided a comprehensive review on NSGA-II algorithm for selected multi-objective combinatorial problems and showed the NSGA-II is the popular metaheuristic algorithm to solve the multi-objective optimization problems. Moreover, the MCNSGA-II algorithm is developed to tackle uncertainty in demand. The results obtained illustrate that the MCNSGA-II algorithm introduced better results than the NSGA-II algorithm.

The paper is structured as follows: In Sect. 2, the related literature is reviewed. The considered problem, its assumption, and the suggested multi-level bi-objective model are defined in Sect. 3 in detail. The solution approach and the computational results are presented in Sects. 4 and 5, respectively. Section 6 contains conclusions and some suggestions for future works.

2 Literature review

The analysis and design of PD systems have been a vital area of research over the years. Geoffrion and Graves (1974) studied a single-period PD problem and suggested a solution approach based on the Benders decomposition algorithm. This is probably the first article to suggest a general mixed-integer programming (MIP) model for the mentioned problem. Haq et al. (1991) utilized an integrated production–inventory–distribution planning formulation in a large fertilizer industry in North India that incorporates many realistic conditions such as lead times, setup cost, and recycling of production losses as well as backlogging. Chen and Wang (1997) suggested an integrated framework for steel PD planning at a major steel producer company in Canada. Ozdamar and Yazgac (1999) introduced a hierarchical PD planning method for a multinational plant with multiple warehouses. Lee and Kim (2000) presented a general PD model in the literature and offered a solution method using a hybrid approach combining analytical and simulation techniques. Varthanan et al. (2012) investigated the PD problem with stochastic demand to minimize regular, overtime, and outsourced production costs. They used a simulation-based heuristic discrete particle swarm optimization (DPSO) algorithm to solve the problem.

Nasiri et al. (2014) suggested a PD model for a three-level program with uncertain demands. They presented a solution framework based on the Lagrangian relaxation algorithm, which is developed by a heuristic to solve subproblems. Niknamfar et al. (2015) considered a three-level SC with multiple production and distribution centers, and different customer areas. They presented a robust counterpart model in PD planning to minimize the total cost. Sarrafha et al. (2015) suggested a bi-objective mixed-integer nonlinear programming (MINLP) formulation to design an SC network that includes suppliers, production and distribution centers, and retailers. They used the multi-objective biogeography-based optimization (MOBBO) algorithm for solving the problem. Seyedhosseini and Ghoreyshi (2015) introduced a mathematical formulation for integrated PD planning for perishable products. An innovative framework is used to solve the formulation in which the suggested method first solves the production problem and afterward, the distribution problem. Devapriya et al. (2017) considered a PD planning problem of a perishable product and provided a MIP model to minimize cost. They presented a solution approach using evolutionary algorithms to solve the model.

Zamarripa et al. (2016) introduced a rolling horizon approach for coordinating the PD of industrial gas SC. Zheng et al. (2016) presented a penalty function-based method to solve a risk-averse PD planning problem. The method changes the formulation into some optimization problems which can be solved by traditional optimization software. Ma et al. (2016) proposed a PD planning model applying bi-level programming for SCM and developed a GA to solve the model. Rezaeian et al. (2016) suggested an MINLP model for the integrated PD and inventory planning for perishable products with a fixed lifetime all over a two-echelon SC by integrating production centers and distributors. Moon et al. (2016) introduced a bi-objective MIP model to design a four-stage distribution system under a carbon emission constraint. They proposed a two-phase method to solve the model and find a non-dominated solution.

Osorio et al. (2017) suggested a simulation–optimization formulation to make strategic and operational decisions in production planning. They used discrete event simulation to demonstrate the flows across the SC, and a MIP model to assist daily decisions. Wei et al. (2017) studied the integrated PD planning problem and presented a model with a two-stage production structure. They applied relax-and-fix and fix-and-optimize approaches to solve the problem. Ensafian and Yaghoubi (2017) considered an SC that consists of procurement, production, and distribution of platelets. They presented a bi-objective mathematical model to maximize the freshness of the platelets and minimize the total cost. Moreover, a robust optimization approach is used to tackle uncertain demand. Farahani and Rahmani (2017) proposed a MIP model that includes production planning, allocation–location facilitation, and distribution planning to maximize the profit of a crude oil network. Nourifar et al. (2018) introduced a multi-period decentralized SC network model with uncertainty. Uncertainty parameters such as demand and final product prices were defined by stochastic and fuzzy numbers. They presented a solution framework based on the Kth-best algorithm, chance constraint approach, and fuzzy approach.

Rafiei et al. (2018) investigated a PD planning problem within a four-echelon SC. The problem is modeled in two non-competitive and competitive markets to minimize total chain cost and maximize service level. Casas-Ramírez et al. (2018) studied an SC, including factories and depots. They proposed a MIP model to balance the total workload and minimize the total cost of the SC. To solve this model, they used an adapted bi-objective GRASP to find non-dominated solutions. Jing and Li (2018) considered a multi-echelon closed-loop SC planning problem involving a joint recycling center, multiple remanufacturing/manufacturing centers, and multiple distribution centers decentralized to various areas. The solution framework was designed by a hierarchical iterative approach based on the self-adaptive GA.

Heidary and Aghaie (2019) proposed a new multi-period and scenario-based supply chain model consisting of several unreliable suppliers, and some retailers. The model is developed in the form of a multi-period newsvendor problem with a risk-averse objective function. They considered risk-sensitive and risk-neutral retailers to tackle uncertain demands and developed a simulation–optimization algorithm to solve the large-scale problem instances. Parnianifard et al. (2020) investigated a dynamic-stochastic production/inventory control system under two uncertainties on-demand rate and frustrating rate. They provided a new computational intelligence approach to evaluate the production/inventory control system by designing robust optimal gain parameters of a proportional–integral–derivative (PID) controller in a stochastic control system. Tao et al. (2020) considered uncertainties and behavioral factors in an integrated procurement and distribution optimization model for a three-tier supply chain. They applied a Monte Carlo simulation-based multi-objective programming model to solve the integrated optimization problem. A normalized normal constraint-based algorithm is adopted to achieve the Pareto frontier.

Goodarzian et al. (2021) studied a novel multi-objective formulation is devised for the PD problem of a supply chain that consists of several suppliers, manufacturers, distributors, and different customers. Due to the NP-hardness of problems, NSGA-II and Fast PGA algorithms are applied. Pant et al. (2021) developed a bi-objective CLSC model for the paper industry under an uncertain environment. The first objective of the proposed model is to maximize SC surplus, and the second objective is to incorporate sustainability through minimizing carbon content by reducing the number of trucks between various echelons of the CLSC network. Aazami and Saidi-Mehrabad (2021) suggested a multi-period PD planning for a three-level SC, including the factories, distribution centers and retailers. The factories and distribution centers act cooperatively at the leader level and, as the seller, make the location, production, inventory, and distribution decisions to maximize the seller's profit. They presented a hierarchical heuristic approach based on Benders decomposition (BD) algorithm and GA. Nishizaki et al. (2022) focused on the PD planning problem in supply chain management. They considered a two-level programming problem where the distributer is the leader and the manufacturer is the follower. The manufacturer's problem minimizing the total cost is formulated as a data envelopment analysis (DEA) production problem from the distributor's viewpoint. The reviewed articles on integrated production–distribution planning are summarized in Table 1.

The last row of Table 1 is for the present study. To the best of our knowledge, there is a gap that motivates us to search in this regard. Specifically, the followings are the significant contributions of this paper:

- A three-level bi-objective programming model is presented to maximize profit and minimize the amount of greenhouse gas emissions.
- NSGA-II algorithm is developed to solve the bi-objective model at each level.
- A hierarchical iterative approach is applied to solved the three-level model.
- NSGA-II algorithm is combined with MC simulation (MCNSGA-II) to tackle uncertainty in demand.

3 Mathematical modeling

In this research, a three-level bi-objective programming model is presented for a GCLSC, which includes multiple recycling centers, multiple manufacturing/remanufacturing factories, and multiple distributors.

Multi-level programming is an optimization approach that has a multilayer hierarchical form. In this form, decision-makers of different levels have various decision-making authorities and objectives. The set of strategies and the goal attainment of lower levels can be affected by the decisions from the upper levels. Nevertheless, lower levels have considerable autonomy, so the upper levels cannot control them (Jing and Li 2018). Regarding the basic concept of multi-level programming, each subordinate level in this model is situated in a different region and has its policies and strategies. The first-level decision-maker (recycling centers) sets its own goals and/or decisions, and then asks each subordinate level of the organization for their optima, which is calculated in isolation. Because of it, Multi-level programming is used.

In the considered GCLSC, returned products are disassembled to components in the multiple recycling centers. Testing activities to know the defective components perform in the centers. The components can be saved in the inventory of eligible components if they have a remanufacturing standard; otherwise, they will be excreted. Eligible components are carried to various remanufacturing/manufacturing centers.

The remanufacturing/manufacturing centers test the quality and efficiency of eligible components, or raw materials are converted to new components. Remanufactured and new components are used to produce remanufactured and new products, respectively. The products are added to the inventory of remanufactured and new products and are carried to various distribution centers according to orders.

Each distribution center can select one or more remanufacturing/manufacturing centers for satisfying demand, and provide remanufactured or new products to retailers for sales. Moreover, the returned products from retailers are gathered and recycled by distribution centers and carried to multiple recycling centers. Note that there are several kinds of vehicles to transport parts and products between the GCLSC components.

Furthermore, the assumptions for the considered problem are as follows:

1. The SC is multi-product, multi-period, and multi-level.

Table 1 Representative works on the integrated production–distribution planning

Authors	Year	Product		Period		Objective		Parameter		Uncertain solution method	Solution Method	Software
		Single	Multi	Single	Multi	Single	Multi	Certain	Uncertain			
Geoffrion and Graves (1974)	1974		*	*		*		*			Bender method	Not given
Haq et al. (1991)	1991		*		*	*		*			Exact	Not given
Chen and Wang (1997)	1997		*	*		*		*			Exact	Not given
Ozdamar and Yazgac (1999)	1999		*		*	*		*			Exact	GAMS
Lee and Kim (2000)	2000		*		*	*			*	Simulation	Exact	GAMS
Varthanan et al. (2012)	2012		*		*	*			*	Simulation	DPSO	MATLAB
Nasiri et al. (2014)	2014		*		*	*			*	Stochastic	GA	MATLAB
Niknamfar et al. (2015)	2014		*		*	*			*	Robust fuzzy	Exact	GAMS
Sarrafha et al. (2015)	2015	*			*		*	*			MOPSO, NSGA-II	MATLAB
Seyedhosseini and Ghoreyshi (2015)	2015	*			*	*		*			Heuristic algorithm	MATLAB
Devapriya et al. (2017)	2016	*			*	*		*			GA, MA	MATLAB
Zamarripa et al. (2016)	2016		*		*	*		*			Rolling Horizon Algorithm	GAMS
Zheng et al. (2016)	2016	*		*		*		*			Exact	GAMS
Ma et al. (2016)	2016		*	*		*			*	Fuzzy	GA	MATLAB
Rezaeian et al. (2016)	2016		*		*	*		*			GA, SA	MATLAB
Moon et al. (2016)	2016	*			*		*	*			Exact	CPLEX
Osorio et al. (2017)	2016		*		*	*			*	Simulation	Exact	JAVA
Wei et al. (2017)	2017		*		*	*		*			Exact	CPLEX
Ensafian and Yaghoubi (2017)	2017	*			*		*		*	Robust	Exact	GAMS
Farahani and Rahmani (2017)	2017		*		*	*		*			Exact	GAMS
Nourifar et al. (2018)	2017		*		*	*			*	Stochastic fuzzy	Exact	LINGO
Rafiei et al. (2018)	2018	*			*		*	*			Exact	LINGO
Casas-Ramírez et al. (2018)	2018	*		*			*	*			GRASP	C++

Table 1 (continued)

Authors	Year	Product		Period		Objective		Parameter		Uncertain solution method	Solution Method	Software
		Single	Multi	Single	Multi	Single	Multi	Certain	Uncertain			
Jing and Li (2018)	2018		*		*	*		*			SAGA	MATLAB
Heidary and Aghaie (2019)	2019	*			*		*		*	Simulation	GA and Q learning	MATLAB
Parnianifard et al. (2020)	2020	*			*	*			*	Stochastic	PSO, GWO, and SOCI	MATLAB
Tao et al. (2020)	2020	*		*			*		*	Monte Carlo Simulation	The Normalized Normal Constraint method	CPLEX
Goodarzian et al. (2021)	2021		*		*		*	*			NSGA-II and Fast PGA	MATLAB
Pant et al. (2021)	2021		*		*		*		*	Monte Carlo Simulation	Augmented epsilon method	MATLAB
Aazami and Saidi-Mehrabad (2021)	2021	*			*	*		*			BD and GA	GAMS and MATLAB
Nishizaki et al. (2022)	2022		*	*	*			*			DEA	GUROBI
Present study	2022		*		*		*		*	Monte Carlo Simulation	LP-metric, NSGA-II and MCNSGA-II	GAMS and MATLAB

2. Demand for remanufactured and new products is uncertain and can only be met by themselves, and remanufactured products have lower selling prices than new products.
3. The production cost of each factory is different.
4. Vehicles have variable capacity at each level.
5. The cost of transfer between the nodes is different.
6. Processing and reprocessing parts in the manufacturing/remanufacturing factories lead to greenhouse gas emissions into the environment.
7. The transportation of vehicles at each level in each period has a greenhouse gas emissions limit (Fig. 1).

Figure 1 shows a schematic of the considered SC.

The notations are introduced in Tables 14, 15, 16, 17, 18, 19, 20 Appendix. The model of each level is as below.

3.1 The recycling centers, the first level

The bi-objective MIP model at the first level (FLM) to maximize profit and minimize adverse environmental effects is as follows:

$$\begin{aligned}\max F_1^R = {} & \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{t=1}^{T} \mathrm{PPC}_{kict}\cdot af_{kicvt} \\ & - \left\{ \sum_{j=1}^{J}\sum_{k=1}^{k}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} \mathrm{URCC}_{jkpt}\cdot da_{jkpvt} \right. \\ & + \sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{SDT}_{kpt}\cdot \sigma_{kpt} + \sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{UDTC}_{kpt}\cdot dt_{kpt} \\ & + \sum_{k=1}^{K}\sum_{c=1}^{C}\sum_{t=1}^{T} \mathrm{UDC}_{kct}\cdot d_{kct} + \sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{ICRP}_{kpt}^{R}\cdot \alpha_{kpt}^{R} \\ & + \sum_{k=1}^{K}\sum_{c=1}^{C}\sum_{t=1}^{T} \mathrm{ICQC}_{kct}^{R}\cdot \beta_{kct}^{R} \\ & \left. + \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{t=1}^{T} \mathrm{UTC}_{kicvt}^{RF}\cdot af_{kicvt} \right\}\end{aligned} \tag{1}$$

$$\min F_2^R = \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{t=1}^{T} \mathrm{dis}_{ki}^{RF}\cdot \mathrm{Emis}_{kicvt}^{RF} . af_{kicvt} \tag{2}$$

$s.t.$

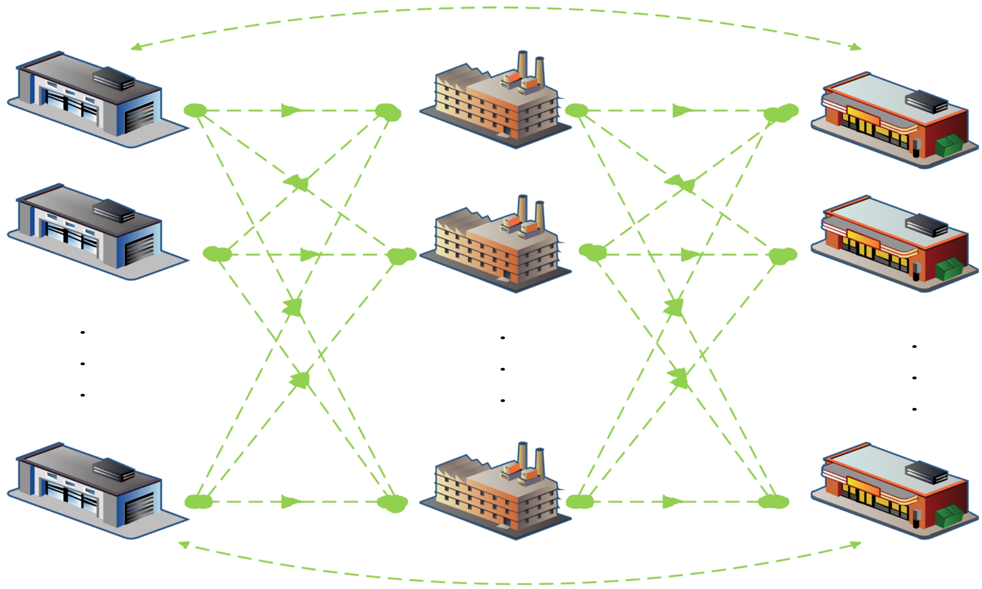


Fig. 1 The schematic of the considered GCLSC Moon et al. (2016)

$$\alpha^R_{kpt} = \alpha^R_{kp,t-1} + \sum_{j=1}^{J}\sum_{v=1}^{V} da_{jkpvt} - dt_{kpt} \quad \forall k,p,t \tag{3}$$

$$\beta^R_{kct} = \beta^R_{kc,t-1} + \sum_{p=1}^{P} BOC_{pc}.dt_{kpt} - d_{kct} - \sum_{i=1}^{I}\sum_{v=1}^{V} af_{kicvt} \quad \forall k,c,t \tag{4}$$

$$\sum_{p=1}^{P} BOC_{pc}.dt_{kpt}.(1-\theta_{kct}) \le d_{kct} \quad \forall k,c,t \tag{5}$$

$$\alpha^R_{kpt} \le \overline{\alpha}^R_{kp} \quad \forall k,p,t \tag{6}$$

$$\beta^R_{kct} \le \overline{\beta}^R_{kc} \quad \forall k,c,t \tag{7}$$

$$dt_{kpt} \le MDT^R_{kp}.\sigma_{kpt} \quad \forall k,p,t \tag{8}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{t=1}^{T} af_{kicvt} \le cap^{RF}_v \quad \forall v \tag{9}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{v=1}^{V} dis^{RF}_{ki}.Emis^{RF}_{kicvt}.af_{kicvt} \le TE^{\max RF}_t \quad \forall t \tag{10}$$

$$af_{kicvt}, da_{jkpt}, dt_{kpt}, d_{kct}, \alpha^R_{kpt}, \beta^R_{kct} \ge 0 \ \& \ \in Z \quad \forall k,i,p,c,v,t \tag{11}$$

$$\sigma_{kpt} \in \{0,1\} \quad \forall k,p,t \tag{12}$$

Equation (1) maximizes the profit of the recycling centers. The profit is equal to revenue minus total costs, including recycling, disassembly, testing, disposal, inventory, and transportation costs. The objective function (2) minimizes the amount of greenhouse gas emissions of each vehicle per kilometer for a unit of eligible components between the recycling centers and remanufacturing/manufacturing factories. Equations (3) and (4) are the inventory equations for returned products and eligible components. Equation (5) shows the quantity equation for disposed of components. Equations (6) and (7) ensure that the inventory rate of returned products and eligible components do not exceed the maximum level. Equation (8) represents that the quantity of returned products to be disassembled and tested in a recycling center does not exceed the maximum amount. Equation (9) guarantees that the quantity of eligible components that are transported by a vehicle from the recycling centers to the remanufacturing/manufacturing factories does not exceed the capacity of the vehicle. Equation (10) ensures the sum of greenhouse gas emissions for the transportation system between recycling centers and factories does not exceed the maximum allowance. Equations (11) and (12) describe the value ranges of the variables.

3.2 The manufacturing/remanufacturing centers, the second level

The bi-objective MIP model at the second level (SLM) to maximize profit and minimize adverse environmental effects is as follows:

$$\begin{aligned}\max F_1^F = &\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} MPN_{ijpt}\cdot fdn_{ijpvt} \\ &+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} MPR_{ijpt}\cdot fdr_{ijpvt} \\ &-\Bigg\{\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}(SA_{ipt}\cdot\eta_{ipt}+UAC_{ipt}\cdot x_{ipt}) \\ &+\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{t=1}^{T}(SP_{ict}\cdot\pi_{ict}+UPC_{ict}\cdot w_{ict}) \\ &+\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}(SRA_{ipt}\cdot\delta_{ipt}+URAC_{ipt}\cdot y_{ipt}) \\ &+\sum_{c=1}^{C}(SRP_{ict}\cdot\tau_{ict}+URPC_{ict}\cdot z_{ict}) \\ &+\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}(ICNP_{ipt}^F\cdot\lambda_{ipt}^F+ICRMP_{ipt}^F\cdot x_{ipt}^F) \\ &+\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{t=1}^{T}\left(ICQC_{ict}^F\cdot\beta_{ict}^F+ICNC_{ict}^F\cdot\zeta_{ict}^F+ICRC_{ict}^F\cdot\xi_{ict}^F\right) \\ &+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T}(UTC_{ijpvt}^{FD}\cdot fdn_{ijpvt}+UTC_{ijpvt}^{FD}\cdot fdr_{ijpvt}) \\ &+\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{t=1}^{T}PPC_{kict}\cdot af_{kicvt}\Bigg\}\end{aligned} \tag{13}$$

$$\begin{aligned}\min F_2^F = &\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} dis_{ij}^{FD}Emis_{ijpvt}^{FD}\cdot(fdn_{ijpvt}+fdr_{ijpvt}) \\ &+\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{t=1}^{T}Emispnc_{ict}^F\cdot w_{ict} \\ &+\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{t=1}^{T}Emisprc_{ict}^F\cdot z_{ict}\end{aligned} \tag{14}$$

$s.t.$

$$\beta_{ict}^F=\beta_{ic,t-1}^F+\sum_{k=1}^{K}\sum_{v=1}^{V}af_{kicvt}-z_{ict}\quad\forall i,c,t \tag{15}$$

$$\zeta_{ict}^F=\zeta_{ic,t-1}^F+W_{ict}-\sum_{p=1}^{P}BOC_{pc}.x_{ipt}\quad\forall i,c,t \tag{16}$$

$$\xi_{ict}^F=\xi_{ic,t-1}^F+z_{ict}-\sum_{p=1}^{P}BOC_{pc}.y_{ipt}\quad\forall i,c,t \tag{17}$$

$$\lambda_{ipt}^F=\lambda_{ip,t-1}^F+x_{ipt}-\sum_{j=1}^{J}\sum_{v=1}^{V}fdn_{ijpvt}\quad\forall i,p,t \tag{18}$$

$$x_{ipt}^F=x_{ip,t-1}^F+y_{ipt}-\sum_{j=1}^{J}\sum_{v=1}^{V}fdr_{ijpvt}\quad\forall i,p,t \tag{19}$$

$$\beta_{ict}^F\le\overline{\beta}_{ic}^F\quad\forall i,c,t \tag{20}$$

$$\zeta_{ict}^F\le\overline{\zeta}_{ic}^F\quad\forall i,c,t \tag{21}$$

$$\xi_{ict}^F\le\overline{\xi}_{ic}^F\quad\forall i,c,t \tag{22}$$

$$\lambda_{ipt}^F\le\overline{\lambda}_{ip}^F\quad\forall i,p,t \tag{23}$$

$$x_{ipt}^F\le\overline{x}_{ip}^F\quad\forall i,p,t \tag{24}$$

$$w_{ict}\le MP_{ic}.\pi_{ict}\quad\forall i,c,t \tag{25}$$

$$z_{ict}\le MRP_{ic}.\tau_{ict}\quad\forall i,c,t \tag{26}$$

$$x_{ipt}\le MA_{ip}\eta_{ipt}\quad\forall i,p,t \tag{27}$$

$$y_{ipt}\le MRA_{ip}\delta_{ipt}\quad\forall i,p,t \tag{28}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}(fdn_{ijpvt}+fdr_{ijpvt})\le cap_v^{FD}\quad\forall v \tag{29}$$

$$\begin{aligned}&\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}dis_{ij}^{FD}.Emis_{ijpvt}^{FD}.(fdn_{ijpvt}+fdr_{ijpvt})\\&\quad\le TE_t^{\max FD}\quad\forall t\end{aligned} \tag{30}$$

$$\begin{aligned}&\sum_{i=1}^{I}\sum_{c=1}^{C}Emispnc_{ict}^F.w_{ict}+\sum_{i=1}^{I}\sum_{c=1}^{C}Emisprc_{ict}^F.z_{ict}\\&\quad\le OPE_t^{\max F}\quad\forall t\end{aligned} \tag{31}$$

$$\begin{aligned}&fdn_{ijpvt},fdr_{ijpvt},af_{kicvt},x_{ipt},y_{ipt},w_{ict},z_{ict},\beta_{ict}^F,\zeta_{ict}^F,\xi_{ict}^F,\lambda_{ipt}^F,x_{ipt}^F\\&\quad\ge 0\ \&\in Z\quad\forall i,j,p,c,v,t\end{aligned} \tag{32}$$

$$\pi_{ict},\tau_{ict},\eta_{ipt},\delta_{ipt}\in(0,1)\quad\forall i,c,p,t \tag{33}$$

Equation (13) maximizes the profit of the remanufacturing/manufacturing factories. The profit is equal to sales revenue minus total costs, including manufacturing, remanufacturing, inventory, purchase, and transportation costs. The objective function (14) minimizes the amount of greenhouse gas emissions of each vehicle per kilometer for a unit of new products and remanufactured products between remanufacturing/manufacturing factories and distribution centers, as well as the amount of greenhouse gas emissions during processing and reprocessing. Equations (15)-(19) represent the inventory equations for eligible, new, remanufactured components, and products. Equations (20)-(24) ensure that the inventory quantities of eligible, new, remanufactured components and products do not exceed the maximum quantity. Equations (25)-(28) guarantee that the quantity of processed and reprocessed components, as well as the quantity of new and remanufactured products, does not exceed the capacity of relevant factories. Equation (29) considers that the amount of new and remanufactured products that are transported by a vehicle from the manufacturing/remanufacturing factories to distribution centers does not exceed the capacity of the vehicle. Equation (30) ensures the sum of greenhouse gas emissions for the transportation system between factories and distributions centers does not exceed the maximum allowance. Equation (31) represents that the sum of greenhouse gas emissions for processing and reprocessing operations in factories must be less than the maximum allowance. Equations (32) and (33) describe the value ranges of the variables.

3.3 The Distribution centers, the third level

The bi-objective MIP model at the third level (TLM) to maximize profit and minimize adverse environmental effects is as below:

$$\begin{aligned}\max F_1^D =& \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} SPN_{jpt}\cdot(DNM_{jpt}-nss_{jpt})\\ &+\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} SPR_{jpt}\cdot(DRM_{jpt}-rss_{jpt})\\ &+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} URCC_{jkpt}\cdot da_{jkpvt}\\ &-\Bigg\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T}(MPN_{ijpt}\cdot fdn_{ijpvt}+MRN_{ijpt}\cdot fdr_{ijpvt})\\ &+\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} URCD_{jpt}\cdot\gamma_{jpt}\\ &+\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}(USNP_{jpt}\cdot nss_{jpt}+USRP_{jpt}\cdot rss_{jpt})\\ &+\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}(ICNP^D_{jpt}\cdot\lambda^D_{jpt}+ICRMP^D_{jpt}\cdot x^D_{jpt}+ICRP^d_{jpt}\cdot\alpha^D_{jpt})\\ &+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} UTC^{DR}_{jkpvt}\cdot da_{jkpvt}\Bigg\}\end{aligned} \tag{34}$$

$$\min F_2^D = \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} dis^{DR}_{jk} Emis^{DR}_{jkpvt}.da_{jkpvt} \tag{35}$$

$s.t.$

$$\lambda^D_{jpt}=\lambda^D_{jp,t-1}+\sum_{i=1}^{I}\sum_{v=1}^{V} fdn_{ijpvt}-(DNM_{jpt}-nss_{jpt}) \quad \forall j,p,t \tag{36}$$

$$x^D_{jpt}=x^D_{jp,t-1}+\sum_{i=1}^{I}\sum_{v=1}^{V} fdr_{ijpvt}-(DRM_{jpt}-rss_{jpt}) \quad \forall j,p,t \tag{37}$$

$$\alpha^D_{jpt}=\alpha^D_{jp,t-1}+\gamma_{jpt}-\sum_{k=1}^{K}\sum_{v=1}^{V} da_{kjpvt} \quad \forall j,p,t \tag{38}$$

$$\gamma_{jpt}\le EPA_{jpt} \quad \forall j,p,t \tag{39}$$

$$nss_{jpt}\le DNM_{jpt} \quad \forall j,p,t \tag{40}$$

$$rss_{jpt}\le DRM_{jpt} \quad \forall j,p,t \tag{41}$$

$$\lambda^D_{jpt}\le\overline{\lambda}^D_{jp} \quad \forall j,p,t \tag{42}$$

$$x^D_{jpt}\le\overline{x}^D_{jp} \quad \forall j,p,t \tag{43}$$

$$\alpha^D_{jpt}\le\overline{\alpha}^D_{jp} \quad \forall j,p,t \tag{44}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} da_{jkpvt}\le cap^{DR}_v \quad \forall v \tag{45}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{v=1}^{V} dis^{DR}_{jk}.Emis^{DR}_{jkpvt}.da_{jkpvt}\le TE_t^{\max DR} \quad \forall t \tag{46}$$

$$nss_{jpt}, rss_{jpt}, da_{jkpvt}, fdn_{ijpvt}, fdr_{ijpvt}, \gamma_{jpt}, \lambda^D_{jpt}, x^D_{jpt}, \alpha^D_{jpt} \ge 0 \ \& \in Z \quad \forall i,j,p,v,t \tag{47}$$

Equation (34) maximizes the profit of the distribution centers. The profit is equal to sales revenue minus total costs, including the purchase of new and returned products, shortage, inventory, and transportation costs. The objective function (35) minimizes the amount of greenhouse gas emissions of each vehicle per kilometer for a unit of returned product between distribution and recycling centers. Equations (36)-(38) show the inventory equations for new, remanufactured, and returned products. Equation (39) ensures that the number of collected returned products does not exceed the number of returned products available in the market. Equations (40) and (41) represent the quantity shortage for new and remanufactured products. Equations (42)-(44) guarantee that the inventory rate of remanufactured, new, and returned products does not exceed the maximum level. Equation (45) ensures that the quantity of returned products, which are transported by a vehicle from distribution centers to recycling centers, does not overstep the capacity of the vehicle. Equation (46) guarantees that the sum of greenhouse gas emissions for the transportation system between distribution and recycling centers does not exceed the maximum allowance. Equation (47) defines the value ranges of the variables.

4 Solution approach

Multi-level linear programming is NP-hard (Hansen et al. 1992), so finding its solutions are usually hard. In this paper, the proposed three-level bi-objective programming formulation is solved based on a hierarchical iterative approach using the LP-metric method for small-size instances and the NSGA-II algorithm for large-size instances, respectively. Moreover, the NSGA-II algorithm is combined with MC simulation (MCNSGA-II) to tackle uncertainty in demand.

4.1 LP-metric method

LP-metric is a classical approach that is applied to solve multi-objective models. The method attempts to find the best solution, which has the shortest distance from the ideal solution. Therefore, the LP-metric function (48) is applied to compute the distance of an available solution to the ideal solution (Pasandideh et al. 2015).

$$Lp = \left\{ \sum_{j=1}^{k} w_j \times \left[\frac{f_j(x^{*j}) - f_j(x)}{f_j(x^{*j}) - f_j(\bar{x}^j)} \right]^p \right\}^{\frac{1}{p}} \tag{48}$$

where $f_j(x)$ and w_j represent the j^{th} objective function and its importance degree, respectively. p demonstrates the emphasis degree on available deviations. To calculate the ideal value of the j^{th} objective function ($f_j(x^{*j})$), the model with the j^{th} objective function and the existing constraints is solved. Moreover, to find the anti-ideal value of the j^{th} objective function ($f_j(\bar{x}^j)$), the objective function is reversed. Finally, we minimize the LP-metric function (48) subject to the constraints to obtain the solution.

4.2 The NSGA-II algorithm

The NSGA-II algorithm (Deb et al. 2002) is applied for solving the considered bi-objective models at each level. The first steps of NSGA-II are encoding and creating the initial population. After the first generation, elitism is introduced, whereby the population is compared to the best previously obtained non-dominated solution. To create a new population, binary selection based on crowding distance and non-domination is used, followed by crossover and mutation. This type of crowded distance sorting is applied using the crowding distance values that measure the objective space around the solution that is not occupied by any other solution in that population Kheiri (2018).

4.2.1 Encoding

Regarding the characteristic of the FLM, $(af_{kicvt}, dt_{kpt}, d_{kct})$ and $(\alpha^R_{kpt}, \beta^R_{kct}, \sigma_{kpt})$ are considered as the decision variables and the state variables, respectively. To encode the solution of the FLM, each decision variable is a part of the chromosome, that generates chromosomes $C^n_{m=1} = (af_{kicvt}, dt_{kpt}, d_{kct})^n_{m=1}$. $n = \{1, 2, \ldots, Npop\}$ indicates the index of population size, $Npop$ is the population size, $m = \{1, 2, \ldots, Maxiter\}$ indicates the index of generation, $Maxiter$ is the maximum number of the generation.

Accordingly, by considering $(fdn_{ijpvt}, fdr_{ijpvt}, x_{ipt}, y_{ipt}, w_{ict}, z_{ict}, subc_{ict})$ as the decision variables, and $(\beta^F_{ict}, \zeta^F_{ict}, \xi^F_{ict}, \pi_{ict}, \tau_{ict}, \eta_{ipt}, \delta_{ipt})$ as the state variables in the SLM as well as $(nss_{jpt}, rss_{jpt}, da_{jkpvt}, \gamma_{jpt})$ as the decision variables, and $(\lambda^D_{jpt}, x^D_{jpt}, \alpha^D_{jpt})$ as the state variables in the TLM, the chromosomes of the levels are defined similarly to the FLM. Due to the suggested model, the values of decision variables in the chromosomes are randomly generated based on the introduced intervals in Table 2, 3, 4.

4.2.2 Crossover

The crossover operator is used to transfer the same characteristics from parents to next-generation children. The simplest types of crossovers are single-point, two-point, and uniform crossover. In this study, the two-point crossover is applied. First, two parents are selected, and then two numbers are randomly selected to determine the cutoff area. The first child inherits the cut region from the second parent, and the second child inherits it from the first parent. Figure 2 shows the crossover operator in this study.

4.2.3 Mutation

The mutation operator is usually performed with a very low probability. In the present study, two chromosomes from the parents are randomly selected, and the position of the two chromosomes is changed, as shown in Fig. 3.

4.3 The hierarchical iterative approach

The proposed three-level model is solved based on a hierarchical iterative algorithm. The description of the algorithm is as below:

Step 1: Determine the initial value of the variable da_{jkpvt}. It is randomly generated from Eqs. (45) and (46) at iteration 0 ($Iter = 0$).

Step 2: Solve the FLM using the values of da_{jkpvt}. Note that the values da_{jkpvt} are from Step 1 and Step 4 in the $(Iter - 1)^{th}$ iteration when $Iter = 0$ and $Iter > 0$, respectively. The LP-metric method is used to solve the FLM and obtain a solution set $(af_{kicvt}, dt_{kpt}, d_{kct}, \alpha^R_{kpt}, \beta^R_{kct}, \sigma_{kpt})^{Iter}$ and

Table 2 Generation interval of decision variables for the FLM

Variables	Generation interval
af_{kicvt}	$unif\left[0,\ \min\left(cap^{RF}_v, \frac{TE^{\max RF}_t}{dis^{RF}_{ki}.Emis^{RF}_{kicvt}}\right)\right]$
dt_{kpt}	$unif[0,\ MDT^R_{kp}]$
d_{kct}	$unif[0,\ round((1-\theta_{kct}).dt_{kpt})]$

Table 3 Generation interval of decision variables for the SLM

Variables	Generation interval
fdn_{ijpvt}, fdr_{ijpvt}	$unif\left[0,\ \min\left(\frac{cap_v^{FD}}{2}, \frac{TE_t^{\max FD}}{2.dis_{ij}^{FD}.Emis_{ijpvt}^{FD}}\right)\right]$
x_{ipt}	$unif[0,\ MA_{ip}]$
y_{ipt}	$unif[0,\ MRA_{ip}]$
w_{ict}	$unif\left[0,\ \min(MP_{ic}, \frac{OPE_t^{\max F}}{2.Emispnc_{ict}^F})\right]$
z_{ict}	$unif\left[0,\ \min(MRP_{ic}, \frac{OPE_t^{\max F}}{2.Emisprc_{ict}^F})\right]$
$subc_{ict}$	$unif[0,\ w_{ict}]$

Table 4 Generation interval of decision variables for the TLM

Variables	Generation interval
nss_{jpt}	$unif[0,\ DNM_{jpt}]$
rss_{jpt}	$unif[0,\ DRM_{jpt}]$
da_{jkpvt}	$unif\left[0,\ \min\left(cap_v^{DR}, \frac{TE_t^{\max DR}}{dis_{jk}^{DR}.Emis_{jkpvt}^{DR}}\right)\right]$
γ_{jpt}	$unif[0,\ EPA_{jpt}]$

its LP-metric function value (F_1^{Iter}). The values af_{kicvt} will be considered for the SLM as a parameter.

Step 3: Solve the SLM using the values af_{kicvt} from Step 2. The LP-metric method is applied to solve SLM and obtain a solution set $(fdn_{ijpvt}, fdr_{ijpvt}, x_{ipt}, y_{ipt}, w_{ict}, z_{ict}, subc_{ict}, \beta_{ict}^F, \zeta_{ict}^F, \xi_{ict}^F, \pi_{ict}, \tau_{ict}, \eta_{ipt}, \delta_{ipt})^{Iter}$ and its LP-metric function value (F_2^{Iter}), in which the values fdn_{ijpvt} and fdr_{ijpvt} will be considered for the TLM as parameters.

Step 4: Solve the TLM applying the values of fdn_{ijpvt} and fdr_{ijpvt} from Step 3. The LP-metric method is used to solve the TLM and obtain a solution set $(nss_{jpt}, rss_{jpt}, da_{jkpvt}, \gamma_{jpt}, \lambda_{jpt}^D, x_{jpt}^D, \alpha_{jpt}^D)^{Iter}$ and its LP-metric function value (F_3^{Iter}), in which the values of da_{jkpvt} will be considered for the FLM as a parameter in a conceivable new iteration.

Step 5: Check that the stopping condition has been met, that is:

$$\max\left(\overline{w_1}, \overline{w_2}, \overline{w_3}\right) \le w^* \tag{49}$$

$$\overline{w_1} = \left|\frac{F_1^{Iter+1} - F_1^{Iter}}{F_1^{Iter+1}}\right|,\ \overline{w_2} = \left|\frac{F_2^{Iter+1} - F_2^{Iter}}{F_2^{Iter+1}}\right|,\ \overline{w_3} = \left|\frac{F_3^{Iter+1} - F_3^{Iter}}{F_3^{Iter+1}}\right| \tag{50}$$

where w^* is an iteration accuracy given in advance. If so, stop iteration; if not, start Step 2.

Note that the NSGA-II algorithm is implemented in the context of the above procedure. The NSGA-II is a population-based algorithm, so the Mean Ideal Distance (MID) criterion is applied to calculate $\overline{w}_1$, $\overline{w}_2$, and $\overline{w}_3$.

$$MID_l = \frac{\sum_{n=1}^{N_l}\sqrt{\left(\frac{f1_{ln} - f1_{l\_best}}{f1_{l\_\max} - f1_{l\_\min}}\right)^2 + \left(\frac{f2_{ln} - f2_{l\_best}}{f2_{l\_\max} - f2_{l\_\min}}\right)^2}}{N_l},\quad \forall\, l = 1, 2, 3 \tag{51}$$

$$\overline{w_1} = \left|\frac{MID_1^{Iter+1} - MID_1^{Iter}}{MID_1^{Iter+1}}\right|,\quad \overline{w_2} = \left|\frac{MID_2^{Iter+1} - MID_2^{Iter}}{MID_2^{Iter+1}}\right|,\quad \overline{w_3} = \left|\frac{MID_3^{Iter+1} - MID_3^{Iter}}{MID_3^{Iter+1}}\right| \tag{52}$$

where $f1_{l\_best}$ and $f2_{l\_best}$ are the ideal point of the first and the second objective functions at the level l. $f1_{l\_\max}$ and $f2_{l\_\max}$ are defined as the largest value of the two objective functions in the obtained non-dominated solutions at the level l. $f1_{l\_\min}$ and $f2_{l\_\min}$ are defined as the smallest value of the two objective functions in the obtained non-dominated solutions at the level l. $f1_{ln}$ and $f2_{ln}$ are the value of the two objective functions of the n^{th} non-dominated solution at the level l. N_l indicates the number of the non-dominated solutions at the level l. Figure 4 displays the hierarchical iterative approach.

4.4 Monte Carlo simulation

MC simulation is premier to a deterministic simulation of a system when the input variables of the system are random. In this simulation approach, a single value is selected for each input random variable based on the best guess by the

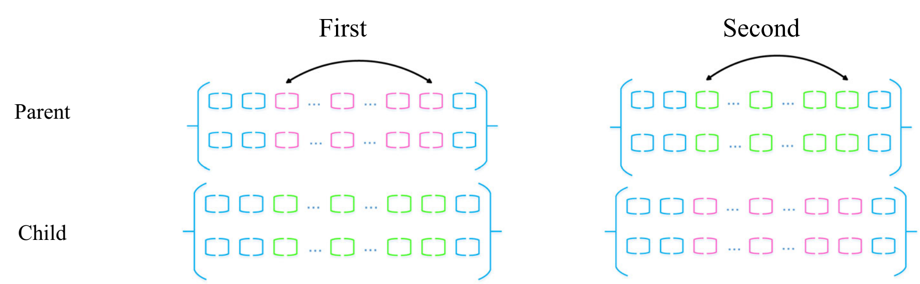


Fig. 2 Crossover operator

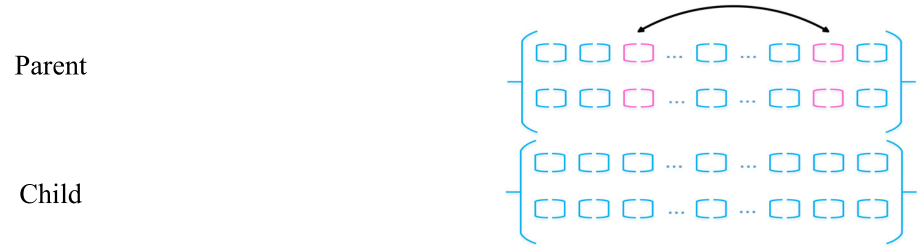


Fig. 3 Mutation operator

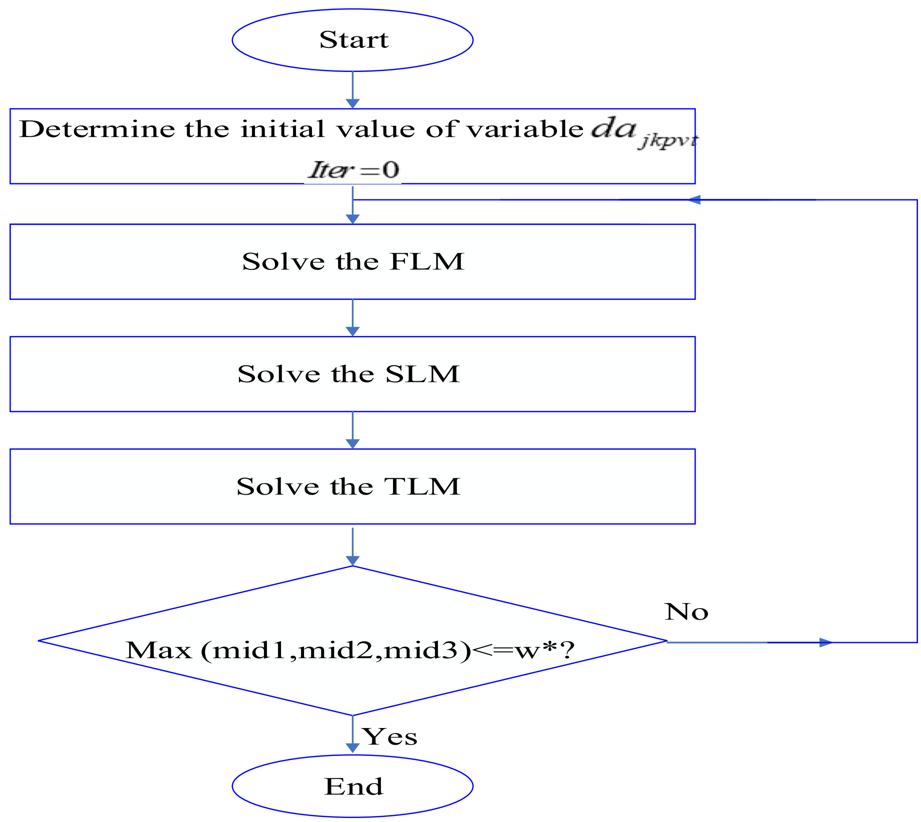


Fig. 4 Flowchart of the hierarchical iterative approach

modeler. The approach is then run, and the output is considered. This output is a single value or a single set of values based on the selected input. MC simulation randomly samples values from every input variable distribution and applies the sample to compute the model's output. This procedure is iterated many times until the modeler achieves a sense of how the output changes given the random input values (Sokolowski and Banks 2010).

In this research, it is assumed that the demand parameter in the third level (distribution centers) is uncertain. We use MC simulation to deal with the uncertainty in the NSGA-II algorithm. Therefore, MC simulation is applied to appraise the objective functions of each chromosome, considering the probability distribution of the demand that is obtained from historical data. Moreover, the expected value of each objective function related to a chromosome is estimated by simulation. Moreover, we calculate the number of simulation iterations using Eq. (53).

$$\Omega \geq \left[z_{\alpha/2} \cdot \frac{S}{E} \right]^2 \tag{53}$$

where Ω is the number of iterations, E is the desired margin of error, and S denotes the computed standard deviation of the output. Furthermore, $z_{\alpha/2}$ shows the critical value of the normal distribution for $\alpha/2$ (Brandimarte 2014).

Figure 5 displays the flowchart of the MCNSGA-II algorithm to generate a Pareto set in the third level.

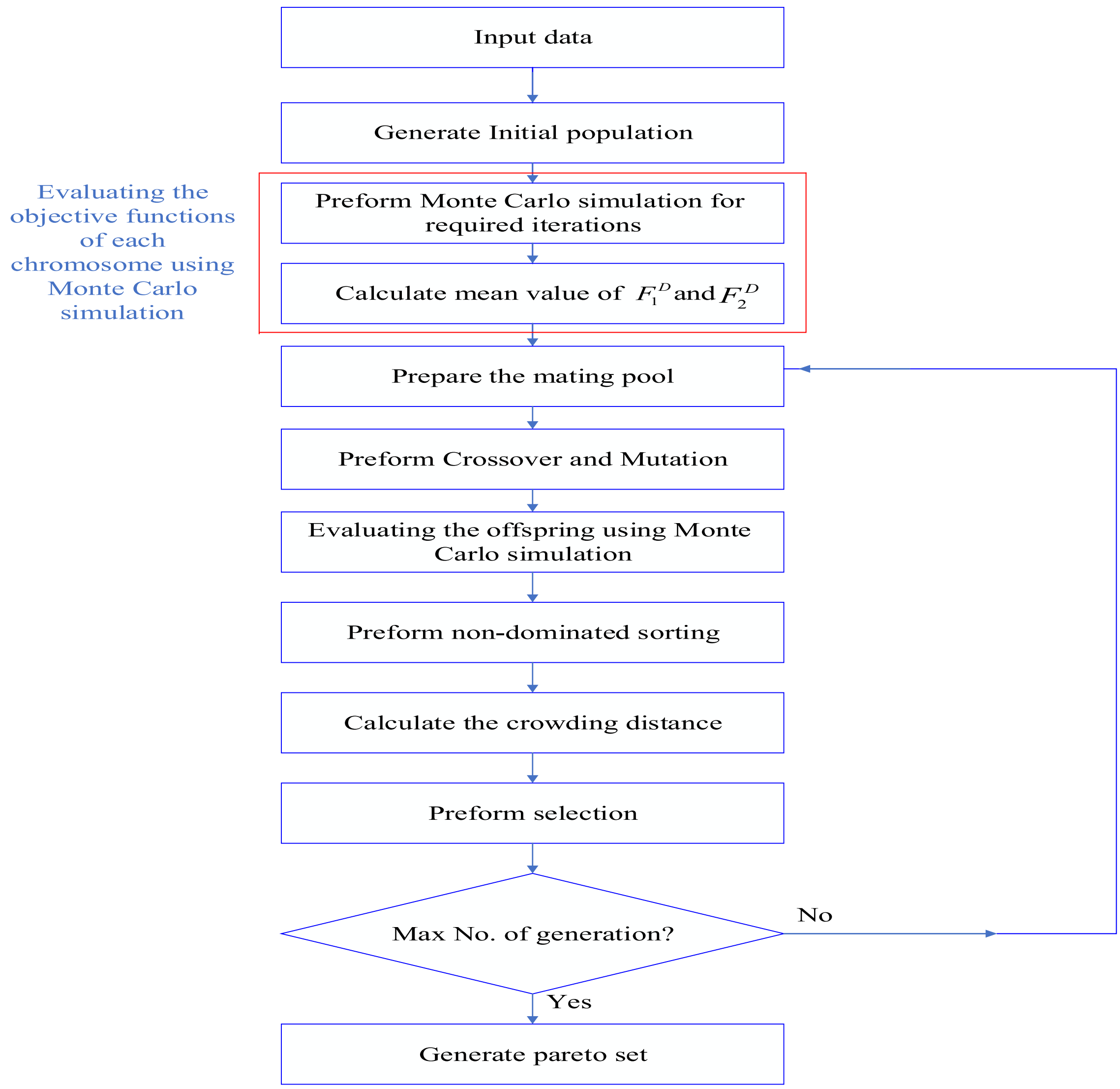


Fig. 5 Flowchart of the MCNSGA-II algorithm in the third level

4.5 Comparison of multi-objective solution methods

Two metrics, set coverage and spacing, are usually applied to evaluate the convergence and diversity of a multi-objective solution method. We apply the following metrics to assess the obtained non-dominated solutions of the NSGA-II and MCNSGA-II algorithms.

4.5.1 Set coverage metric

Zitzler and Thiele (1999) proposed the set coverage metric $C(A,B)$ that computes the ratio of solutions in B and is weakly dominated by solution A.

$$C(A,B) = \frac{|\{b \in B | \exists a \in A : a \leq b\}|}{|B|} \tag{54}$$

where $C(A,B) = 1$ means that all members of B are weakly dominated by A. $C(A,B) = 0$ shows that no member of B is weakly dominated by A.

4.5.2 Spacing metric

Scott (1995) presented the following metric to calculate the comparative distance between successive solutions in the non-dominated set (Q).

$$S = \sqrt{\frac{1}{Q}\sum_{i=1}^{|Q|} \left(d_i - \overline{d}\right)^2} \tag{55}$$

where $d_i = \min_{k \in Q \wedge k \neq i} \sum_{m=1}^{M} \left|f_m^i - f_m^k\right|$, M indicates the number of objective functions, f_m^i and f_m^k are the i^{th} and k^{th}

Table 5 Dimension of the test problems

Index	Level		
	Small	Medium	Large
Number of recycling centers (k)	[2,4]	[5,7]	≥ 8
Number of manufacture/remanufacture factories (i)	[2,4]	[5,7]	≥ 8
Number of distributions (j)	[2,5]	[6,8]	≥ 9
Number of components (c)	[2,6]	[7,9]	≥ 10
Number of products (p)	[2,3]	[4,6]	≥ 7
Number of vehicles (v)	[2,4]	[6,7]	≥ 8
Number of periods (t)	[2,7]	[8,12]	≥ 12

Table 6 Values of model parameters

First-level parameters	Second-level parameters	Third-level parameters
$PPC_{kict} = Uniform\,(200, 400)$	$SA_{ipt} = Uniform\,(60, 70)$	$SPN_{jpt} = Uniform\,(20000, 30000)$
$URCC_{jkpt} = Uniform\,(100, 200)$	$SRA_{ipt} = Uniform\,(40, 60)$	$SPR_{jpt} = Uniform\,(10000, 20000)$
$SDT_{kpt} = Uniform\,(50, 60)$	$UAC_{ipt} = Uniform\,(55, 65)$	$DNM_{jpt} = Uniform\,(30, 50)$
$UDTC_{kpt} = Uniform\,(45, 50)$	$URAC_{ipt} = Uniform\,(45, 55)$	$DRM_{jpt} = Uniform\,(15, 18)$
$UDC_{kct} = Uniform\,(20, 30)$	$SP_{ict} = Uniform\,(70, 80)$	$URCD_{jpt} = Uniform\,(30, 60)$
$ICQC^{R}_{kct} = Uniform\,(10, 20)$	$SRP_{ict} = Uniform\,(65, 70)$	$USNP_{jpt} = Uniform\,(53, 75)$
$ICRP^{R}_{kpt} = Uniform\,(10, 20)$	$MPN_{ijpt} = Uniform\,(700, 900)$	$USRP_{jpt} = Uniform\,(33, 45)$
$UTC^{RF}_{kicvt} = Uniform\,(40, 60)$	$MPR_{ijpt} = Uniform\,(600, 700)$	$ICNP^{D}_{jpt} = Uniform\,(17, 27)$
$\theta_{kct} = Uniform\,(0.85{,}0.95)$	$UPC_{ict} = Uniform\,(65, 75)$	$ICRM^{D}_{jpt} = Uniform\,(16, 26)$
$\overline{\alpha}^{R}_{kp} = Uniform\,(200, 250)$	$URPC_{ict} = Uniform\,(60, 70)$	$ICRP^{D}_{jpt} = Uniform\,(15, 25)$
$\overline{\beta}^{R}_{kc} = Uniform\,(200, 250)$	$ICNP^{F}_{ipt} = Uniform\,(15, 25)$	$UTC^{DR}_{jkpt} = Uniform\,(50, 66)$
$MDT^{R}_{kp} = Uniform\,(1150, 1200)$	$ICRMP^{F}_{ipt} = Uniform\,(15, 25)$	$EPA_{jpt} = Uniform\,(180, 200)$
$cap^{RF}_{v} = Uniform\,(350, 400)$	$ICQC^{F}_{ict} = Uniform\,(15, 25)$	$\overline{\lambda}^{D}_{jp} = Uniform\,(100, 110)$
$dis^{RF}_{ki} = Uniform\,(200, 300)$	$ICNC^{F}_{ict} = Uniform\,(10, 15)$	$\overline{x}^{D}_{jp} = Uniform\,(100, 110)$
$Emis^{RF}_{kicvt} = Uniform\,(0.0001{,}0.0007)$	$ICRC^{F}_{ict} = Uniform\,(15, 25)$	$\overline{\alpha}^{D}_{jp} = Uniform\,(100, 110)$
$TE^{\max RF}_{t} = Uniform\,(4000, 7000)$	$UTC^{FD}_{ijpvt} = Uniform\,(46, 63)$	$cap^{DR}_{v} = Uniform\,(350, 400)$
$BOC_{pc} = Uniform\,(1, 4)$	$\overline{\beta}^{F}_{ic} = Uniform\,(95, 100)$	$dis^{DR}_{jk} = Uniform\,(200, 300)$
	$\overline{\zeta}^{F}_{ic} = Uniform\,(95, 100)$	$Emis^{DR}_{jkpvt} = Uniform\,(0.0001{,}0.0007)$
	$\overline{\xi}^{F}_{ic} = Uniform\,(95, 100)$	$TE^{\max DR}_{t} = Uniform\,(4000, 7000)$
	$\overline{\lambda}^{F}_{ip} = Uniform\,(0, 100)$	
	$\overline{x}^{F}_{ip} = Uniform\,(0, 100)$	
	$MA_{ip} = Uniform\,(0, 800)$	
	$MRA_{ip} = Uniform\,(0, 350)$	
	$MP_{ic} = Uniform\,(800, 6400)$	
	$MRP_{ic} = Uniform\,(350, 2800)$	
	$cap^{FD}_{v} = Uniform\,(350, 400)$	
	$dis^{FD}_{ij} = Uniform\,(300, 400)$	
	$Emis^{FD}_{ijpvt} = Uniform\,(0.0001{,}0.0007)$	
	$Emispnc^{F}_{ict} = Uniform\,(5, 10)$	
	$Emisprc^{F}_{ict} = Uniform\,(5, 10)$	
	$OPE^{\max F}_{t} = Uniform\,(7000, 10000)$	
	$TE^{\max FD}_{t} = Uniform\,(4000, 7000)$	

Table 7 Different levels for NSGA-II algorithm parameters at the recycling centers level

Algorithm	Parameters	Parameter range	Level		
			1	2	3
NSGA-II	Maxiter	[100,300]	100	200	300
	N-pop	[50,100]	50	75	100
	Pc	[0.85,0.95]	0.85	0.9	0.95
	Pm	[0.05,0.15]	0.05	0.1	0.15

where Pc and Pm are the crossover and mutation probability, respectively. Then, applying Minitab Software, the L9 design is applied for the NSGA-II algorithm, and experimental results are illustrated in Table 8

value of the objective function m in the set Q, respectively, and $\overline{d} = \sum_{i=1}^{|Q|} d_i/|Q|$. The metric computes the standard deviations of different values; thus, the small value of the metric demonstrates that the solutions are approximately uniformly spaced.

Based on the above-mentioned metrics, an algorithm with a greater C and a smaller S is preferred.

5 Computational results

In this section, numerical experiments are conducted to investigate the performance of the three-level bi-objective MIP model, the NSGA-II algorithm, and the MCNSGA-II algorithm based on random data. First, we present how the test problems are generated. The Taguchi approach is then employed to tune the parameters of the NSGA-II algorithm, and the best level of each parameter is obtained by the signal-to-noise diagram in the Minitab software. Sensitivity analysis is then performed for different weights of LP-metric function, and the best weight for each level is selected. The results obtained by the LP-metric method and the NSGA-II algorithm are compared, and the relative distance of each sample is determined. Note that the LP-metric method and the NSGA-II algorithm are implemented in GAMS and MATLAB, respectively, and are tested on a computer with a 2.3 GHz CPU and 8.0 GB of RAM. Finally, the MCNSGA-II algorithm is implemented on two instances, and the results are compared with the NSGA-II algorithm.

5.1 Data generation

We need to test the suggested mathematical model and the solution approach using randomly generated test problems. The dimension of the test problems that are categorized into small, medium, and large scale is introduced in Table 5.

Moreover, the values of model parameters are randomly generated based on a uniform distribution that are shown in Table 6.

5.2 Parameter tuning of NSGA-II

The Taguchi experimental design approach is utilized to calibrate the parameters of the NSGA-II algorithm. The approach minimizes the effect of noise and specifies the optimal level of signal factors. To do so, the signal-to-noise (S/N) ratio, which computes the value of the variation of the response, is implemented. Then, the method aims to maximize the S/N ratio (Peace 1993). In this study, MID and maximum scattering (MS) metrics calculate response based on Eq. (56).

$$\mathrm{Re}sponse = \frac{MID}{MS} \tag{56}$$

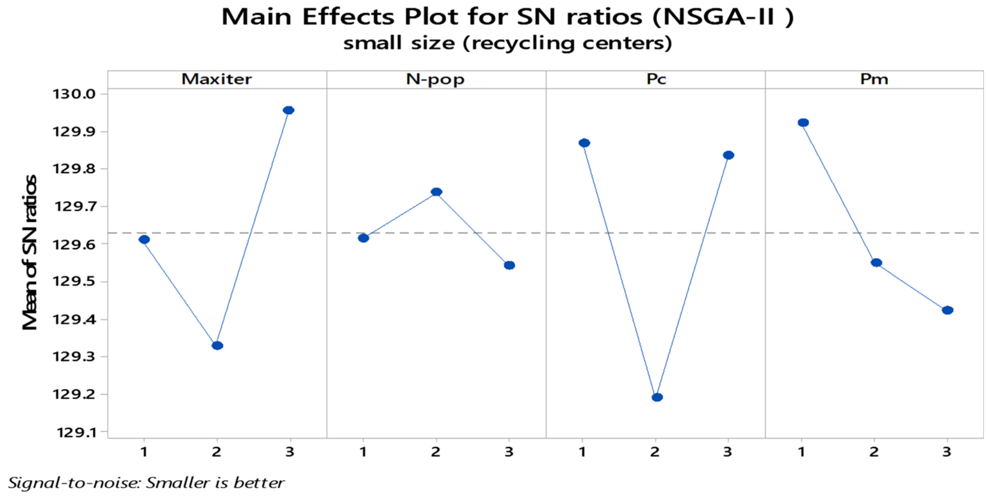
Table 7 exhibits different levels of the factors for NSGA-II algorithm parameters at the recycling centers level to run the Taguchi method.

The above approach is applied to parameter tuning of the NSGA-II algorithm at the second and third levels. Figure 6 indicates the effect plot of the S/N ratio related to

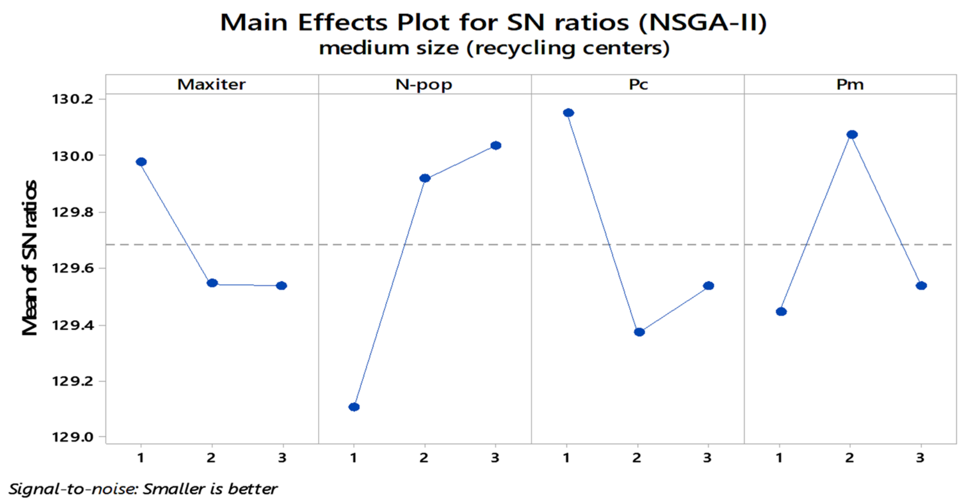
Table 8 L9 design for the NSGA-II algorithm at the recycling centers level

Experiment	Maxiter	N-pop	Pc	Pm	Response		
					Small (10^{-7})	Medium (10^{-7})	Large (10^{-7})
1	1	1	1	1	3.11793	3.30369	3.71324
2	1	2	2	2	3.47064	3.06284	3.46838
3	1	3	3	3	3.34403	3.15414	3.20768
4	2	1	2	3	3.68890	3.75809	3.16742
5	2	2	3	1	3.18804	3.39505	3.43168
6	2	3	1	2	3.38996	2.90125	3.37563
7	3	1	3	2	3.13996	3.46964	3.31004
8	3	2	1	3	3.13142	3.13068	3.21475
9	3	3	2	1	3.26834	3.41561	3.08207

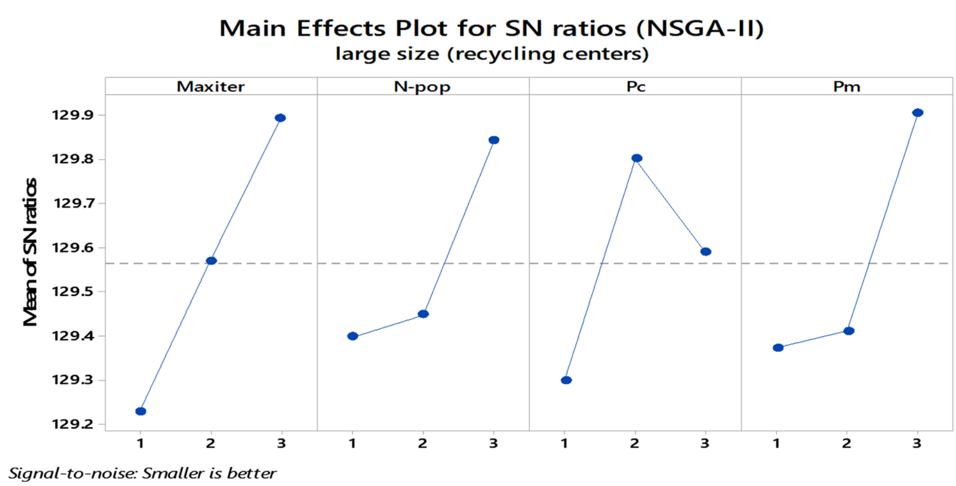
Fig. 6 S/N ratios



(a) Small size- Recycling centers

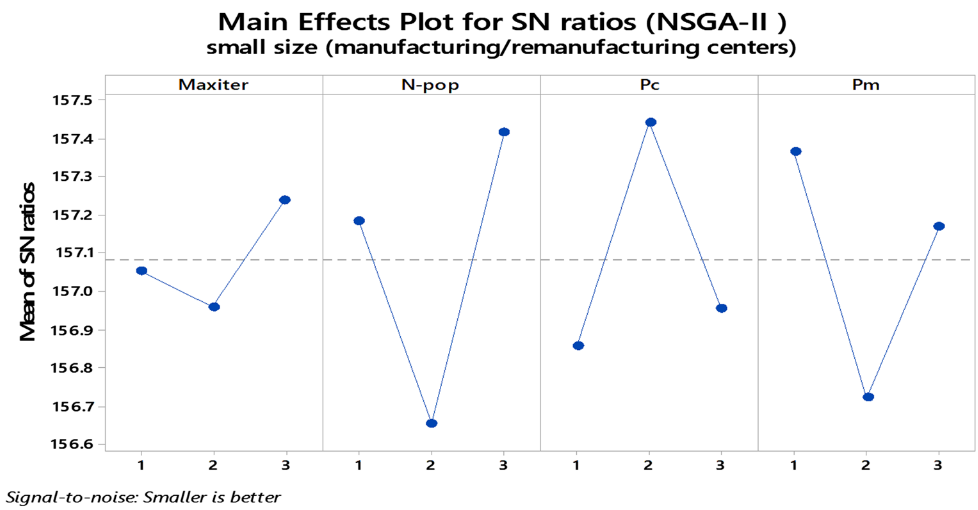


(b) Meduim size- Recycling centers

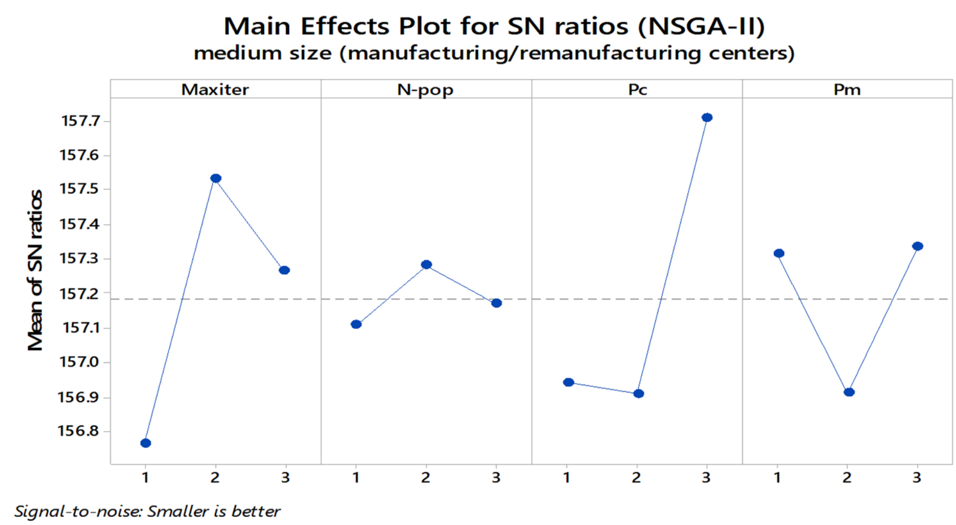


(c) Large size- Recycling centers

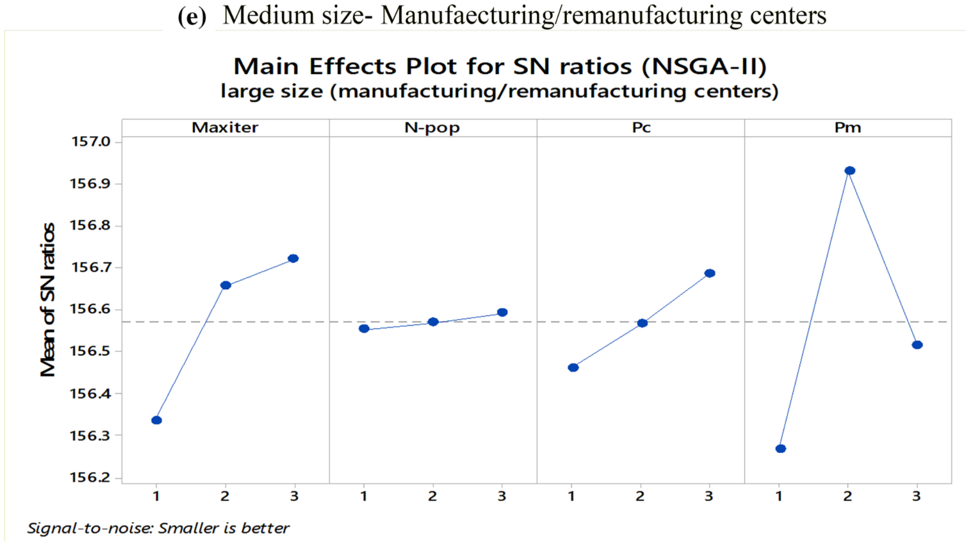
Fig. 6 continued



(d): Small size- Manufacturing/remanufacturing centers

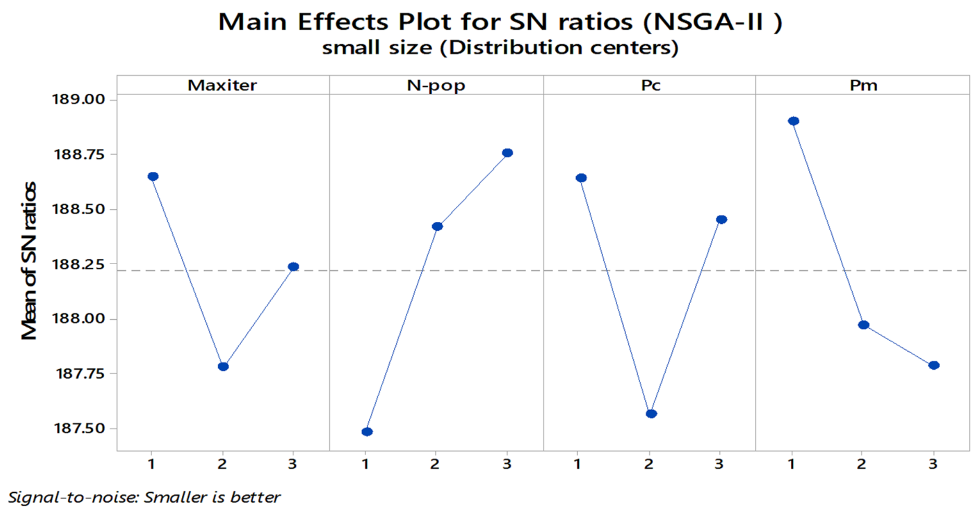


(e) Medium size- Manufaecturing/remanufacturing centers

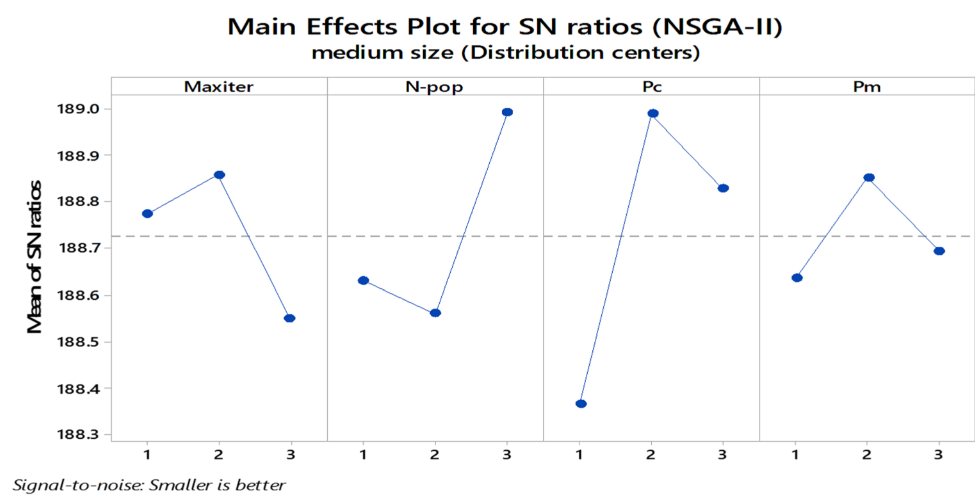


(f) Large size- Manufaecturing/remanufacturing centers

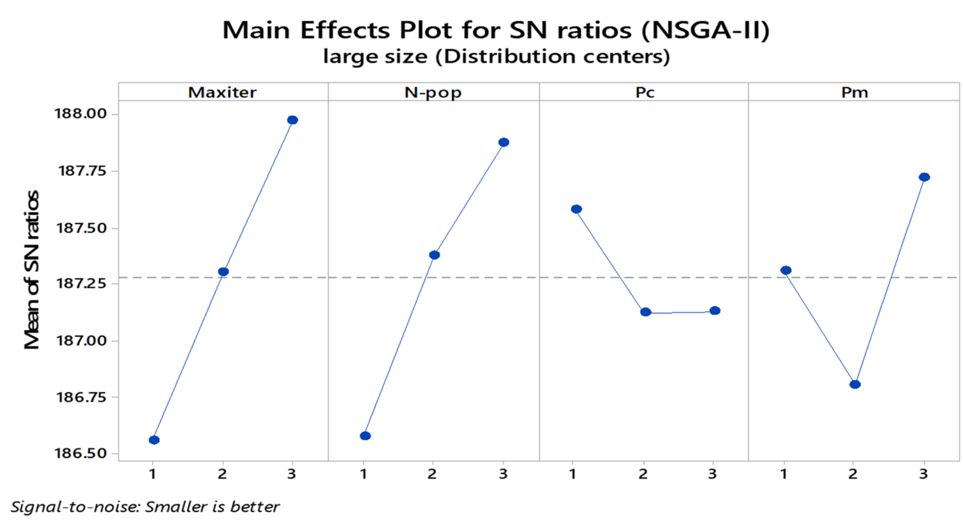
Fig. 6 continued



(g) Small size- Distribution centers



(h) Medium size- Distribution centers



(i) Large size- Distribution centers

Table 9 Best parameter values of the NSGA-II algorithm

NSGA-II	Parameters	Small			Medium			Large		
		Level 1	Level 2	Level 3	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
The recycling centers level	Maxiter			300	100					300
	N-pop		75				100			100
	Pc	0.85			0.85				0.9	
	Pm	0.05				0.1				0.15
The factories level	Maxiter			300		200				300
	N-pop			100		75				100
	Pc		0.9				0.95			0.95
	Pm	0.05					0.15		0.1	
The Distribution centers level	Maxiter	100				200				300
	N-pop			100			100			100
	Pc	0.85				0.9		0.85		
	Pm	0.05				0.1				0.15

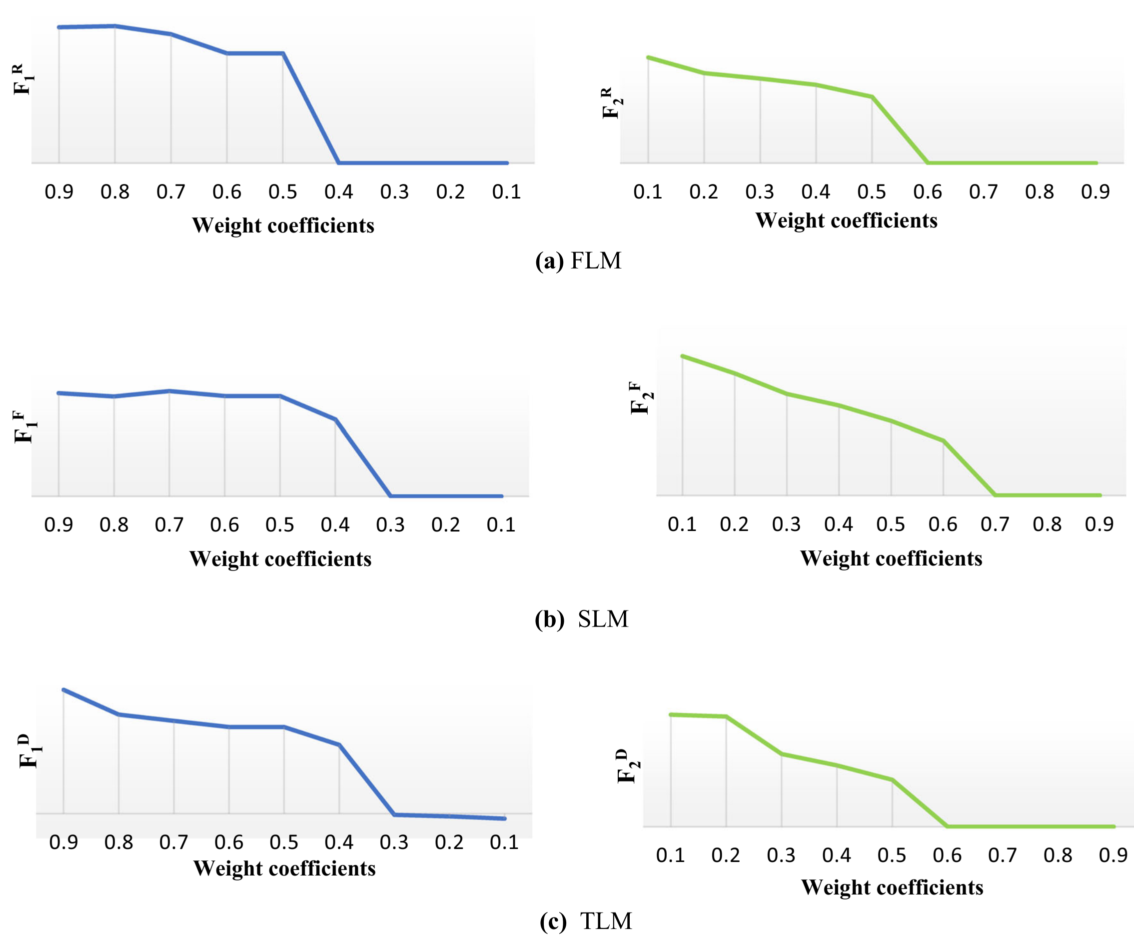


Fig. 7 Different weights in the various levels of the problem

Table 10 Validation results

Problem	Dimension of the problems	Level	GAMS		NSGA-II		
			LP-metric	CPU Time (S)	LP-metric	CPU Time (S)	Relative GAP
1	$k_2i_2j_2p_2c_2v_2t_2$	1	0.275	5	0.301	73	9%
		2	0.425		0.453		6%
		3	0.267		0.272		1%
2	$k_3i_3j_5p_3c_3v_3t_2$	1	0.028	13	0.0299	98	6%
		2	0.775		0.834		7%
		3	0.093		0.094		1%
3	$k_3i_4j_5p_3c_3v_3t_4$	1	0.379	66	0.411	134	8%
		2	0.647		0.691		6%
		3	0.093		0.095		2%
4	$k_4i_4j_5p_3c_3v_3t_5$	1	0.446	386	0.481	176	7%
		2	0.626		0.679		8%
		3	0.290		0.301		3%
5	$k_4i_4j_5p_3c_4v_3t_6$	1	0.599	410	0.657	241	9%
		2	0.700		0.769		9%
		3	0.145		0.149		2%
6	$k_4i_4j_5p_3c_6v_4t_7$	1	0.553	924	0.602	358	8%
		2	0.813		0.869		6%
		3	0.209		0.216		3%

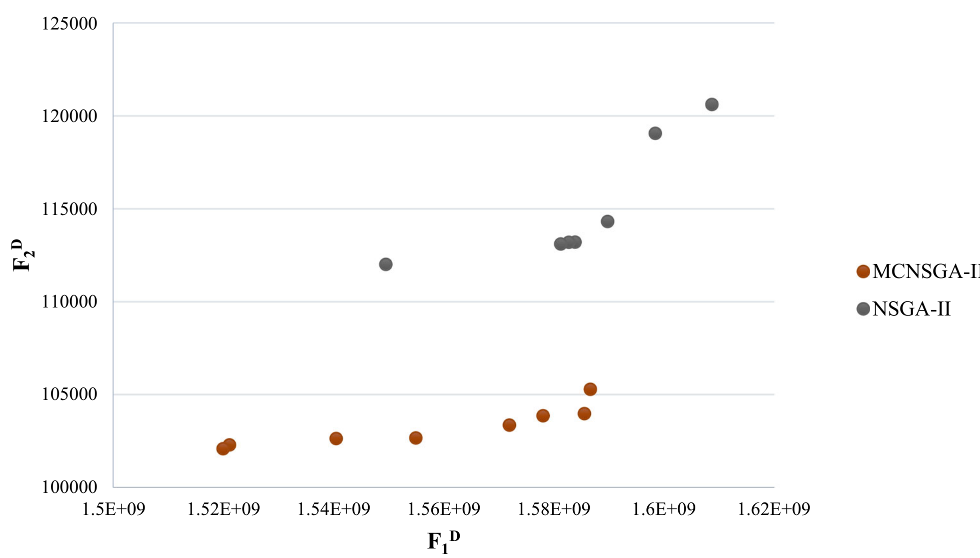


Fig. 8 Comparison between the non-dominated solutions obtained with different optimization methods for a medium-size instance

each level. Figure 6 shows that the mean of S/N ratio is best, so the best parameter values of the NSGA-II algorithm for each level are indicated in Table 9.

5.3 The weight coefficients in LP-metric method

It is necessary to determine the suitable weight coefficients of the objective functions for executing the proposed model in GAMS software based on the LP-metric method. Different weight combinations are solved for a small-size determinant problem, and the appropriate weight is generalized to the other problem. Figure 7 illustrates how the value of the objective functions is affected by various weights in different levels of the problem. The most significant variations in the objective functions happen in the weight coefficients between 0.4 and 0.9, and in the other

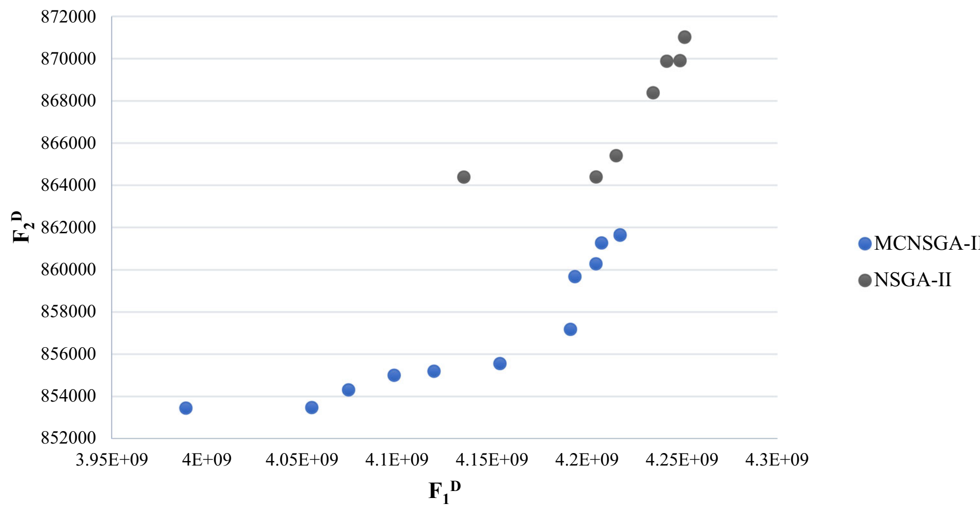


Fig. 9 Comparison between the non-dominated solutions obtained with different optimization methods for a large-size instance

Table 11 Convergence metric (C)

$C(A,B)$	Medium-size instance		Large-size instance	
	NSGA-II	MCNSGA-II	NSGA-II	MCNSGA-II
NSGA-II	–	0	–	0
MCNSGA-II	0.5714	–	0.375	–

Table 12 Spacing metric (S)

S	Medium-size instance		Large-size instance	
	NSGA-II	MCNSGA-II	NSGA-II	MCNSGA-II
	1.01E + 07	5.45E + 06	2.16E + 07	1.82E + 07

weights, the objective function value becomes zero. So, it is better to weigh the goals between these limits. According to Fig. 7, maximizing the first goal is a priority. Thus, the weight of the first objective function is selected for maximization, and consequently, the weight of the second goal function is determined. the weight of 0.8 is chosen for maximizing the first objective function (F_1^R). Hence, the weight of 0.2 for the second objective function (F_2^R) of the FLM. A weight of 0.7 is chosen for maximizing the first objective function (F_1^F). Therefore, a weight of 0.3 for minimizing the second objective function (F_2^F) of the SLM. Moreover, a weight of 0.9 is chosen for maximizing the first objective function (F_1^D) and a weight of 0.1 for the second objective function (F_2^D) of the TLM.

5.4 Validation of the NSGA-II algorithm

The LP-metric method is used for model validation. Thus, six small-scale problems are solved in GAMS software with the LP-metric method. Note that it is not possible for large-scale problems. Moreover, for comparison, the six small problems are solved with the NSGA-II algorithm. Since the NSGA-II is run based on the assumption that the initial population is randomly generated; hence, any test problem is solved ten times. The best non-dominated solution is selected from the ten times of running results, and its LP-metric measure is calculated. The measured value is compared with the value obtained from the exact

Table 13 Sensitivity analysis of demand

Case	DNM_{jpt}	DRM_{jpt}	Level 1: recycling center (MCNSGA-II)		Level 2: manufacturing center (MCNSGA-II)		Level 3: distribution center (MCNSGA-II)	
			F_1^C	F_2^C	F_1^M	F_2^M	F_1^D	F_2^D
1	$U[24, 40]$	$U[12, 14]$	2,512,534,956	2,614,389.61	5,972,044,068	8,439,956.22	6,933,377,002	2,129,386.79
2	$U[30, 50]$	$U[15, 18]$	2,524,445,901	2,633,257.56	6,448,798,189	8,523,444.8	7,332,729,090	2,138,523.65
3	$U[36, 60]$	$U[16, 22]$	2,610,535,986	2,654,479.614	6,572,098,068	8,534,557.18	7,598,777,507	2,354,586.64

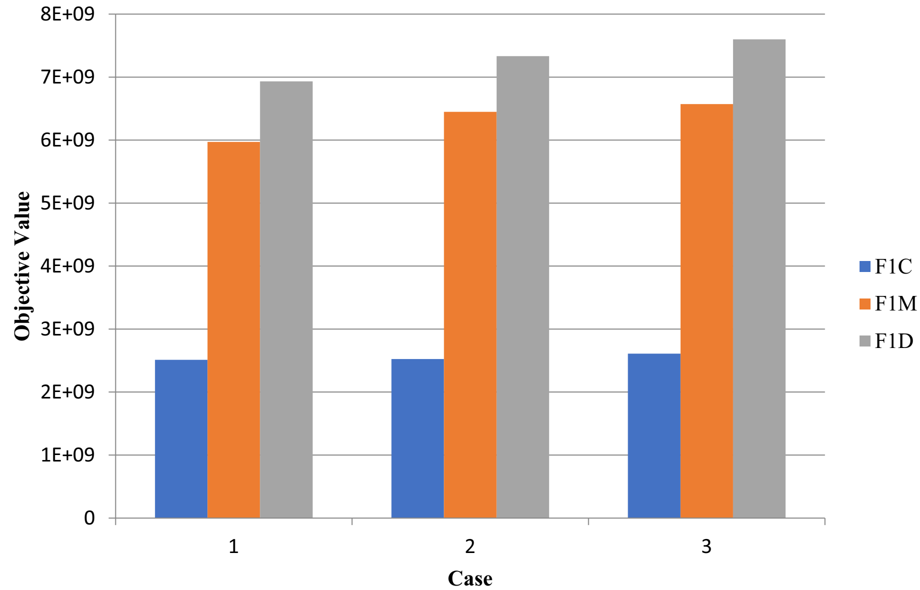


Fig. 10 Value of the first objective in the three levels by considering different demands

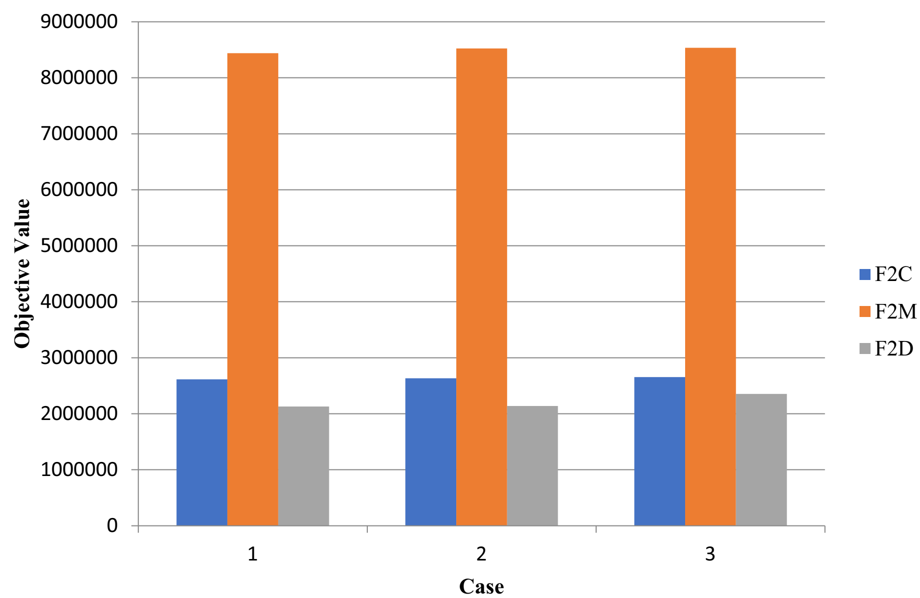


Fig. 11 Value of the second objective in the three levels by considering different demands

method that is run in GAMS. In Table 10, the relative gap between the values of the two LP-metric measures, which are achieved from the exact method and the NSGA-II algorithm, is calculated.

According to Table 10, the average of the relative gaps is 7%, 7%, and 1% for the three levels, respectively. In addition, we can observe that the average run-time of the problem is dramatically increased when the size of the instances grows. The average run-time of the LP-metric method and the NSGA-II algorithm is 300 s and 180 s, respectively. Therefore, we can declare that the NSGA-II algorithm is suitable to solve the considered problem.

5.5 Analysis of MC simulation

In this research, it is assumed that the demands for remanufactured and new products in distribution centers at different periods are stochastic. The probability distribution function associated with the value of demand is uniform. The MC simulation approach is used to deal with the uncertainty.

Equation (53) is used to calculate the number of simulation replications. First, a pilot run of MC simulation is implemented considering an initial sample size of 10 replications to calculate the mean and the standard deviation of F_1^D and F_2^D for a chromosome. By considering a confidence level of 95% and an error of 0.1, the number of simulation replications is obtained equal to eight based on Eq. (53).

The medium- and large-size problems are solved to compare the NSGA-II and MCNSGA-II algorithms. Figures 8, 9 indicate the non-dominated solutions, which are achieved from the NSGA-II and MCNSGA-II algorithms for the medium- and large-size problems. The stochastic demand is the parameter of the third level of the considered SC; thus, the non-dominated solutions of the third level are only shown in Figs. 8, 9. The figures indicated that NSGA-II is dominated by MCNSGA-II. The importance and priority of the two objective functions are different. The first objective is to maximize profit and the second objective is to minimize greenhouse gases emissions. To achieve more profit, more production must be done, and on the other hand, more greenhouse gas is produced both from factory production and in transportation.

Table 11, 12 indicate the value of convergence (C) and spacing (S) metrics of the different optimization methods. If the C metric is larger and the S metric smaller for an algorithm, it shows that the algorithm is more efficient. As can be seen, the MCNSGA-II algorithm presents better non-dominated solutions than the NSGA-II algorithm.

5.6 Sensitivity analysis

In this subsection, we investigate the effect of demand fluctuations on the objective values. Therefore, we consider different interval values for the demand of the new and remanufactured products, and the obtained results of a large-scale instance that is solved by MCNSGA-II are displayed in Table 13.

There is a significant relationship between the amount of demand and the first objectives so that as the amount of demand increases, the value of the first objectives also increases (Fig. 10).

Changes in demand have a straight affect on the second objective which means if the demand increases, consequently, the second objective increase, especially in the second level of the model due to producing emission gas in the manufacture/remanufacture center. However, we aim to reduce the second objective due to being environmentally friendly (Fig. 11).

6 Conclusions

We considered an integrated PD planning problem of a multi-level GCLSC system, that includes multiple recycling centers, multiple remanufacturing/manufacturing centers, and multiple distribution centers. A three-level bi-objective MIP model is presented to maximize profit and minimize the amount of greenhouse gas emissions. A hierarchical iterative approach using the LP-metric method and the NSGA-II algorithm is suggested to solve the proposed model. The Taguchi experimental design approach is applied to find optimum control parameters of NSGA-II. Moreover, the NSGA-II algorithm is fused with MC simulation (MCNSGA-II) to deal with the uncertainty of the product demand in distribution centers. The results obtained show that the simulation–optimization approach presented better results than the deterministic approach.

Furthermore, there are several opportunities for future research. First, to understand the realities of the environment, it is important to consider uncertainty in other influential parameters such as purchase costs and shipping costs. Second, studying the literature on multi-level production–distribution planning shows that fewer study goals, such as customer satisfaction and reduction of delay time in the model, were considered. Adding the aforementioned goals could be of interest for future research. Third, in this and other studies, multi-level planning has been solved at two or three levels. Hence, adding the fourth level as the supplier level can be an appropriate area for future research. Fourth, solving this model with other multi-objective metaheuristic algorithms such as multi-objective particle swarm optimization (MOPSO) algorithm, Pareto simulated annealing (PSA) algorithm, multi-objective gray wolf optimization (MOGWO) algorithm, multi-objective gravitational search algorithm (MOGSA) would be another future scope.

Appendix

See Tables 14, 15, 16, 17, 18, 19, 20.

Table 14 Definition of the sets

T	Set of periods $(t = 1, 2, \ldots, T)$
P	Set of product types $(p = 1, 2, \ldots, P)$
C	Set of component types $(c = 1, 2, \ldots, C)$
V	Set of vehicle types $(v = 1, 2, \ldots, V)$
I	Set of manufacturing/remanufacturing factory $(i = 1, 2, \ldots, I)$
J	Set of distributors $(j = 1, 2, \ldots, J)$
K	Set of recycling centers $(k = 1, 2, \ldots, K)$

Table 15 Parameters of the FLM

PPC_{kict}	Purchase unit cost at period t for eligible component c by factory i from recycling center k
$URCC_{jkpt}$	Recycling unit cost at period t for returned product p from distributor j by recycling center k
SDT_{kpt}	Setup cost at period t for returned product p in recycling center k
$UDTC_{kpt}$	Disassembly and tested unit cost of at period t for returned product p in recycling center k
UDC_{kpt}	Disposing unit cost at period t for component c in recycling center k
$ICQC^{R}_{kct}$	Inventory unit cost at period t for eligible component c in recycling center k
$ICRP^{R}_{kpt}$	Inventory unit cost at period t for returned product p in recycling center k
UTC^{RF}_{kicvt}	Transportation unit cost at period t for eligible component c by vehicle v from recycling center k to factory i
BOC_{pc}	Bill of component c to product p
θ_{kct}	Rate of remanufacturing for component c at period t in recycling center k
$\overline{\alpha}^{R}_{kp}$	The highest inventory quantity of returned product p in recycling center k
$\overline{\beta}^{R}_{kc}$	The highest inventory quantity of eligible components c in recycling center k
MDT^{R}_{kp}	The highest amount of returned product p can be disassembled and tested in the recycling center k in every period
cap^{RF}_{v}	The capacity of vehicle v that goes from recycling centers to manufacturing/remanufacturing factories
dis^{RF}_{ki}	Distance between recycling center k and factory i
$Emis^{RF}_{kicvt}$	Greenhouse gas emissions per unit of eligible component c with vehicle v per kilometer between recycling center k and factory i
$TE^{\max RF}_{t}$	Maximum greenhouse gas emissions allowance for transportation system between recycling centers and factories at period t

Table 16 Parameters of the SLM

MPN_{ijpt}	The average price at period t for new product p paid by distributor j to factory i
MPR_{ijpt}	The average price at period t for remanufactured product p paid by distributor j to factory i
SA_{ipt}	Setup cost at period t to assemble new product p in factory i
SRA_{ipt}	Setup cost at period t to assemble remanufactured product p in factory i
UAC_{ipt}	Assembly unit cost at period t for new product p in factory i
$URAC_{ipt}$	Assembly unit cost at period t for remanufactured product p in factory i
SP_{ict}	Setup cost at period t when component c is processed in factory i
SRP_{ict}	Setup cost at period t when component c is reprocessed in factory i
UPC_{ict}	Processing unit cost at period t for component c in factory i
$URPC_{ict}$	Reprocessing unit cost at period t for component c in factory i
$ICNP^{F}_{ipt}$	Inventory unit cost at period t for new product p in factory i
$ICRMP^{F}_{ipt}$	Inventory unit cost at period t for remanufactured product p in factory i
$ICQC^{F}_{ict}$	Inventory unit cost at period t for eligible component c in factory i
$ICNC^{F}_{ict}$	Inventory unit cost at period t for new component c in factory i
$ICRC^{F}_{ict}$	Inventory unit cost at period t for remanufactured component c in factory i
UTC^{FD}_{ijpvt}	Transportation unit cost at period t for product p by vehicle v from factory i to distributor j
$\overline{\beta}^{F}_{ic}$	The highest inventory quantity of eligible components c in factory i
$\overline{\zeta}^{F}_{ic}$	The highest inventory quantity of new components c in factory i
$\overline{\xi}^{F}_{ic}$	The highest inventory quantity of remanufactured components c in factory i
$\overline{\lambda}^{F}_{ip}$	The highest inventory quantity of new products p in factory i
$\overline{x}^{F}_{ip}$	The highest inventory quantity of remanufactured products p in factory i
MA_{ip}	Maximum capacity of factory i to assemble new product p at each period
MRA_{ip}	Maximum capacity of factory i to assemble remanufactured product p at each period
MP_{ic}	Maximum capacity of factory i to process component c at each period
MRP_{ic}	Maximum capacity of factory i to reprocess component c at each period
cap^{FD}_{v}	The capacity of vehicle v that goes from a manufacturing/ remanufacturing factory to a distributor

Table 16 (continued)

dis^{FD}_{ij}	Distance between factory i and distributor j
$Emis^{FD}_{ijpvt}$	Greenhouse gas emissions per unit of product p with vehicle v per kilometer between factory i and distributor j at period t
$Emispnc^{F}_{ict}$	Greenhouse gas emissions during the processing of each new component c in manufacturing/ remanufacturing factory i at period t
$Emisprc^{F}_{ict}$	Greenhouse gas emissions during the reprocessing of each component c in manufacturing/ remanufacturing factory i at period t
$OPE^{\max F}_{t}$	Maximum greenhouse gas emissions allowance at period t during processing/reprocessing operations in factories
$TE^{\max FD}_{t}$	Maximum greenhouse gas emissions allowance for transportation system between factories and distribution centers at period t
PPC_{kict}	This notation has taken value in the FLM
BOC_{pc}	This notation has taken value in the FLM

Table 17 Parameters of the TLM

SPN_{jpt}	Selling price at period t for new product p in distributor j
SPR_{jpt}	Selling price at period t for remanufactured product p in distributor j
DNM_{jpt}	Demands of new product p at period t in the market of distributor j
DRM_{jpt}	Demands of remanufactured product p at period t in the market of distributor j
$URCD_{jpt}$	Recycling unit cost at period t for returned product p paid by distributor j to retailers or customers
$USNP_{jpt}$	Shortage unit cost at period t for new product p paid by distributor j
$USRP_{jpt}$	Shortage unit cost at period t for remanufactured product p paid by distributor j
$ICNP^{D}_{jpt}$	Inventory unit cost at period t for new product p in distributor j
$ICRM^{D}_{jpt}$	Inventory unit cost at period t for remanufactured product p in distributor j
$ICRP^{D}_{jpt}$	Inventory unit cost at period t for returned product p in distributor j
UTC^{DR}_{jkpvt}	Transportation unit cost at period t for returned product p by vehicle v from distributor j to recycling center k
EPA_{jpt}	Amount of returned product p at period t available in the market of distributor j
$\bar{\lambda}^{D}_{jp}$	The highest inventory quantity of new product p in distributor j
$\bar{x}^{D}_{jp}$	The highest inventory quantity of remanufactured product p in distributor j
$\bar{\alpha}^{D}_{jp}$	The highest inventory quantity of return product p in distributor j
cap^{DR}_{v}	The capacity of vehicle v that goes from distribution to recycling centers
dis^{DR}_{jk}	Distance between distributor j and recycling center k
$Emis^{DR}_{jkpvt}$	Greenhouse gas emissions per unit of product p with vehicle v per kilometer between distributor j and recycling center k at period t
$TE^{\max DR}_{t}$	Maximum greenhouse gas emissions allowance for transportation system between distribution and recycling centers at period t
$URCC_{jkpt}$	This notation has taken value in the FLM
MPN_{ijpt}	This notation has taken value in the SLM
MPR_{ijpt}	This notation has taken value in the SLM

Table 18 Variables of the FLM

af_{kicvt}	Amount of eligible component c that is transported by vehicle v at period t from recycling center k to factory i
da_{jkpvt}	Amount of returned product p that is transported by vehicle v at period t from distributor j to recycling center k
dt_{kpt}	Amount of returned product p at period t that is disassembled and tested in recycling center k
d_{kct}	Amount of component c at period t that is disposed of in recycling center k
α^{R}_{kpt}	Inventory quantity of returned product p at recycling center k at the end of period t
β^{R}_{kct}	Inventory quantity of eligible component c in recycling center k at the end of period t
σ_{kpt}	1 if returned product p at period t is disassembled and tested in recycling center k; 0 otherwise

Table 19 Variables of the SLM

fdn_{ijpvt}	Amount of new product p at period t that is transported by vehicle v from factory i to distributor j
fdr_{ijpvt}	Amount of remanufactured product p at period t that is transported by vehicle v from factory i to distributor j
x_{ipt}	Amount of new product p at period t that is assembled in factory i
y_{ipt}	Amount of remanufactured product p at period t that is assembled in factory i
w_{ict}	Amount of component c at period t that is processed in factory i
z_{ict}	Amount of component c at period t that is reprocessed in factory i
λ^{F}_{ipt}	Inventory quantity of new product p at factory i at the end of period t
x^{F}_{ipt}	Inventory quantity of remanufactured product p in factory i at the end of period t
β^{F}_{ict}	Inventory quantity of eligible component c in factory i at the end of period t
ζ^{F}_{ict}	Inventory quantity of new component c in factory i at the end of period t
ξ^{F}_{ict}	Inventory quantity of remanufactured component c in factory i at the end of period t
η_{ipt}	1 if new product p is assembled by factory i at period t; 0 otherwise
δ_{ipt}	1 if remanufactured product p is assembled by factory i in batches at period t; 0 otherwise
π_{ict}	1 if component c is processed by factory i at period t; 0 otherwise
τ_{ict}	1 if component c is reprocessed by factory i at period t; 0 otherwise
$subc_{ict}$	The amount of one-way substitution for component c at period t in factory i
af_{kicvt}	This notation has taken value in the FLM

Table 20 Variables of the TLM

nss_{jpt}	Amount of new shortage product p at period t in distributor j
rss_{jpt}	Amount of remanufactured shortage product p at period t in distributor j
γ_{jpt}	Amount of returned product p at period t that is collected by distributor j from downstream markets
λ^{D}_{jpt}	Inventory quantity of new product p in distributor j at the end of period t
x^{D}_{jpt}	Inventory quantity of remanufactured product p in distributor j at the end of period t
α^{D}_{jpt}	Inventory quantity of return product p in distributor j at the end of period t
da_{jkpvt}	This notation has taken value in the FLM
fdn_{ijpvt}	This notation has taken value in the SLM
fdr_{ijpvt}	This notation has taken value in the SLM

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Declarations

Conflict of interest The authors declare that they have no conflict of interest regarding the publication of this paper.

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