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A dynamic bi-objective optimization model for a closed loop supply chain design under environmental policies

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Abstract Given the increasing focus on sustainability and environmental policy constraints, companies are required to redesign their supply chains. This paper explores the optimization of a closed loop supply chain (CLSC) network under both economic and environmental considerations. To achieve this, a bi-objective mixed integer linear model was developed. The proposed model identifies the optimal selection of CLSC facilities and manages both forward and reverse flows between them. The economic objective is reached by minimizing the total CLSC costs, while the environmental objective is satisfied by reducing CO2 emissions throughout the network. Products can be returned throughout their entire life cycle, which is why our model incorporates a dynamic aspect by considering product life cycle phases as time periods for the decision horizon. The model was tested through numerical experiments using a meta-heuristic approach based on the non-dominated sorting genetic algorithm NSGA-II. This algorithm produces a set of Pareto-optimal solutions that balance both objectives effectively. The results showed good performance in terms of computational time and optimization. Pareto solutions offered various options for managers and decision makers aiming for a sustainable closed loop supply chain design.

Keywords Closed loop supply chain design, Bi-objective optimization, Reverse logistics, Non- dominated sorting genetic algorithm, Pareto front.

AMS 2010 subject classifications 78M32, 90B50, 90C05, 90C11, 90C29

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1. Introduction

With the growing awareness of natural resource scarcity and the increasing imposition of environmental regulations, companies must rethink their strategies to achieve sustainable operations. This involves redesigning supply chains to incorporate both environmental and economic factors. Consequently, reverse logistics activities, such as the collection and recovery of used products, are added to the traditional supply chain to create a closed loop supply chain (CLSC) [1]. Manufacturers benefit from CLSC by profiting through the remanufacture of returned consumer products. Remanufacturing is often more energy-efficient and can be more profitable and quicker than producing new items in some scenarios [2].

The reverse logistics network exerts considerable impact on the forward logistics network and vice versa, thus necessitating the integrated design of both forward and reverse logistics networks [3]. In fact, the performance of CLSC is directly influenced by the design of the CLSC network, and much of the existing

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literature has focused on addressing the issue of effective CLSC network design [4, 5, 6]. Recent studies have particularly emphasized sustainable CLSC design, evaluating both economic and environmental aspects simultaneously [7, 8]. Within this context, this paper aims to propose a CLSC network design model that integrates forward and reverse flows and considers two optimization criteria: the total cost of the CLSC and the reduction of CO2 emissions throughout the network. Considering the product lifecycle, the CLSC structure is cyclic, with materials and information flowing bidirectionally between network partners. This establishes a value loop that encompasses all stages of the product lifecycle, considered to be the decision-making horizon in our proposed model.

In the realm of supply chain design decisions, the proposed model encompasses both strategic and tactical aspects. Strategic choices involve optimally selecting which facilities to establish and determining which distribution and recycling centers to operate. Tactical choices focus on optimizing the flow of products in both forward and reverse logistics, including product allocation, processing quantities, and the addition or removal of machines or technologies at the operational facilities.

Reviewing the literature on CLSC, various methods have been employed to tackle optimization problems with competing objectives. One of the most commonly used techniques involves transforming a multi-objective problem into a single-objective one using the ϵ-constraint method [9]. To produce an efficient set of Pareto front solutions, the value of ϵ is adjusted within a range that is pertinent to each objective function. Another method is the weighted sum approach, where solutions are derived by optimizing a single-objective problem formed by the weighted sum of different objectives. The weights for each objective are varied multiple times to approximate the Pareto front [10, 11]. This paper adds to the limited number of studies addressing multi-objective CLSC network design problems with metaheuristic approaches by applying the non-dominated sorting genetic algorithm NSGAII. In NSGAII, solutions are evaluated based on non-dominated sorting and crowding distance. Various experiments with different genetic algorithm parameters were conducted to assess the algorithm's performance.

The remainder of the paper is organized as follows. In section 2, Literature review on reverse logistics and closed loop supply chain design is presented. In section 3, the problem definition is described. In section 4, the closed loop supply chain network design optimization model is formulated including assumptions, sets, parameters, objectives and decision variables. Section 5 provides numerical experiments and computational results discussions. Conclusion and future scope are reached in section 6.

2. Literature review

Traditionally, supply chain design focused only on economic aspects (cost minimization or profit maximization), with few or no regards to its environmental impacts [12, 13]. Moreover, in most of works, the supply chain network design is basically studied as location-allocation problem [14, 15]. As result of increasing environmental concerns, traditional supply chains are transformed to green supply chains by integrating reverse logistics processes. Therefore, not only economic aspects are considered but also environmental ones. For instance, Fahimnia et al. (2015) have developed an MINLP model to determine optimal values for products manufactured at different stages of supply chains, the rate of carbon emission and fuel consumption. The model investigated both economic and environmental trade-offs through several scenarios in the manufacturing sector [16]. Bouchery et al. (2017) used multi-objective optimization to tackle the coordination in supply chain in order to reduce the carbon emissions and costs [17]. Kwak and Kim have developed a decision-support model for determining optimal design of new and remanufactured products simultaneously and number of returned products in which the trade-off between total profit and environmental-impact saving was examined [18].

Recently, research studies dealing with reverse logistics and closed-loop supply chain network design have known a significant increase. They highlighted the important value of integrating forward and reverse flows in a CLSC model to achieve more effective reduction in emissions [19]. These studies could be classified in two main categories [20]. A first category involves works that address reverse logistics and CLSC network designing and planning [21, 22]. A second one considered that remanufactured and new products should not be considered separately because of price advantages and included studies on determining optimum products price and return price decision of CLSC [2, 3, 23, 24].

In fact, works of the two categories share the use of multiobjective CLSC models that combine an economic objective with an environmental one. For instance, Ghahremani et al. (2020) proposed a multi-objective model for closed-loop green supply chain network design for multi-products and multi-periods. They addressed the variability in the modeling of CLSC network design considering demand uncertainty and discount [25]. Hasani et al. (2021) provided a comprehensive model to maximize the total profit and minimize the centralization of facilities and amounts of CO2 emission. They considered the tactical level of supply chain design through the selection of transportation modes [26]. Seydanlou et al. (2022), developed a multi-objective optimization framework for a sustainable closed-loop supply chain network in the case of olive industry supply chain. They considered three objectives, namely, minimizing cost, minimizing CO2 emissions and maximizing job opportunities [27].

Regarding uncertainties consideration, few recent works addressed uncertain environment for modeling CLSC network design. Dehshiri et al. (2022) proposed a novel robust fuzzy approach for closed-loop supply chain network design where hybrid uncertainties and flexibility of constraints in the problem were examined. They considered sustainability issues including targets of cost, transport time, and carbon emissions [28]. Han et al. (2024) addressed demand uncertainty in their CLSC model considering an inventory-sharing strategy with continuous approximation approach to solve uncertain demand in their network design [29]. Kchaou-Boujelben et al. (2023) included three types of uncertainties namely: return quantity, return quality and remanufacturing costs. To solve their bi-objective CLSC design problem, they combined the use of NSGA-II genetic algorithm and a linear programming (LP) relaxation [30].

Generally, to solve these complex multi-objective optimization problems, several methods were conducted in the CLSC literature. The most popular method adopted is to convert the problem to single objective optimization using multi-criteria decision-making methods, the ϵ-constraint method [31, 32] or weighted sum and goal programming [11, 15]. Another approach is to use directly multi-objective evolutionary algorithms to find a set of solutions verifying the notion of Pareto optimum [33, 34]. In this paper, we opted for a bi-objective modeling of a CLSC design optimization where a multi-criterion genetic algorithm (GA) of NSGA II type is used to solve the model proposed. Unlike several literature works that have used this type of GA to solve the CLSC design problem, our work study the effects of all GA parameters variation on the objective functions' values conducting several computational simulations. This is for seeking the optimal values of GA parameters leading to solution optimization.

This paper differs from the previous works by the following considerations:

- Forward and reverse flow are simultaneously integrated for the CLSC design.
- Returned products could be either final products or components and they are integrated into the forward chain to cover final demands.
- The model proposed covers the strategic and tactical levels at once.
- The suggested model is dynamic and considers product life cycle phases as time periods for Horizon decision. This is for considering the variability of demand during the entire lifecycle of the product.

3. Problem description

We considered a four-level supply chain network consisting of components' suppliers at the first level, production and remanufacturing plants at the second level, distribution centres at the third level and customers at the fourth level (figure 1). In the forward channel, the supply chain consists of suppliers, production plants, distribution centres and customers. In the reverse channel, products at the end of their life cycle are returned by end customers and received in remanufacturing plants where they are sorted then recovered through recycling and remanufacturing. It is assumed that products coming out remanufacturing plants could be either final products or components.

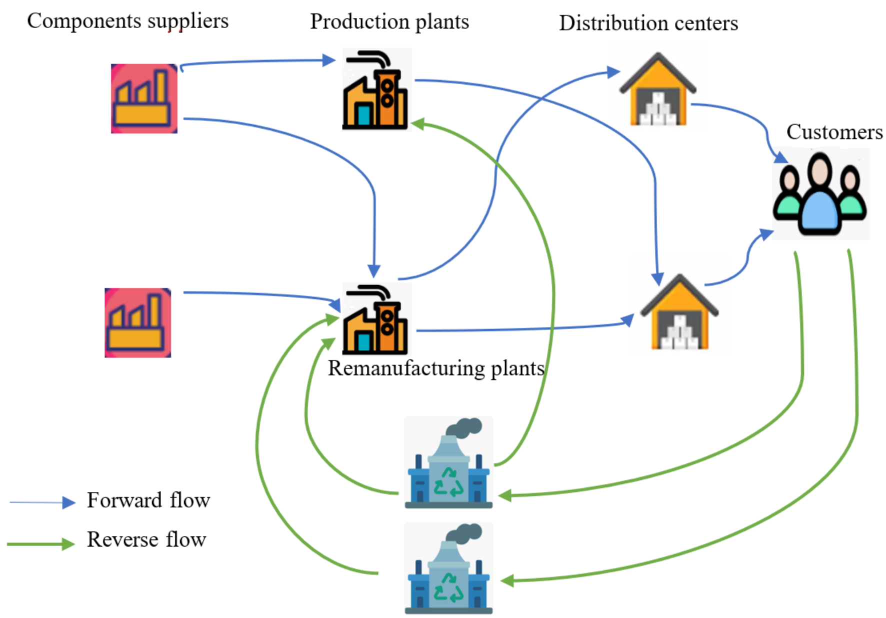

Figure 1. Structure of CLSC network considered.

Given that there are sets of potential suppliers, production plants, distribution centers and remanufacturing plants, the objective at the strategic of the model proposed is to seek for the optimal selection of those to be opened and operated. At the tactical level, the aim of the model is to precise products allocation with amounts produced at each facility and to determine manufacturing and remanufacturing machines to be added or removed. These decisions are taken in a way to minimize the total costs and the carbon emission from forward and reverse flows. The model formulation is detailed in the next section.

4. Model formulation

In this section, we first present the problem assumptions, define input parameters and decision variables then explain the objective functions and constraints.

4.1. Problem assumptions

The considered assumptions are as follows:

- Demand for components and final products is known.
- Only one mode of transportation is considered.
- Distribution centers assure storage, holding and transportation of finished products.
- Remanufacturing plants could return either components or final products to production plants.
- All manufacturing/remanufacturing technologies (machines) added must not exceed a maximum number in a way to satisfy plants capacity and investment budgets.

4.2. Problem sets and data

Before we present the mathematical model, we present sets definition in Table 1 then characterize the notations of parameters that are used throughout the model in Table 2.

Table 1. Sets definition

Notation	Description
C	Set of components, indexed by c
S	Set of suppliers, indexed by s
P	Set of producing plants indexed by p
M, N	Sets of production/remanufacturing machines required for processing the product P indexed by m and n respectively
D	Set of distribution centers indexed by d
K	Set of customers indexed by k
R	Set of recycling centers indexed by r
T	Decision horizon indexed by t[2pt]

Table 2. Problem Parameters

Parameter	Description
$CA_{c,s,t}$	Purchasing unit cost of supplier s for the component c in period t.
$CT_{c,s,t}$	Transport mileage cost of supplier s for the component c in period t.
$CS_{c,p}$	Storage unit cost of the component c in plant p.
$Dis_{s,p}, Dis_{p,d}, Dis_{d,k}, Dis_{k,r}, Dis_{r,p}$	Distances between supplier s and producing plant p/producing plant p and distribution center d/distribution center d and client k/client k and center r/remanufacturing center r and producing plant p.
$CF_{s,p,t}$	Partnership fixed cost of the supplier s with plant p in period t.
$d_{c,p,t}$	Demand for component c in plant p in period t.
$Capmax_{s,c,t}$	Maximum capacity of the supplier s to deliver the component c in period t.
$Chp_{m,t}$	Production hourly unit cost of the product in the machine m in period t.
$CFA_{m,t}$	Fixed cost of machine m implementation in period t.

Parameter	**Description**
$CTD_{p,d,t}$	Transportation mileage cost of product from plant p to a distributor d.
$CFR_{m,t}$	Removal or jobless cost of the machine m in period t.
$Chr_{n,t}$	Recycling hourly unit cost of the product in the machine n in period t.
$Chrc_{c,n,t}$	Recycling hourly unit cost of the component c in the machine n in period t.
$CFRA_{n,t}$	Fixed cost of recycling technology n implementation in period t.
$CFRS_{n,t}$	Removal or jobless cost of recycling technology n in period t.
$D_{k,t}$	Demand of the customer k for the final product in period t.
$Caprod_{m,t}$	Maximum capacity of the machine m in period t.
tpu_m	Production unit time of the product in a machine m in period t.
$NEI_{m,p}$	Number of copies of a machine m originally existing at producing plant p.
$MaxNE_{m,p,t}$	Maximum number allowed to be added for machine m to plant p in period t.
$Caprecy_{n,t}$	Recycling maximum capacity of the machine n in period t.
$CF_{r,p}$	Contracting cost related to selection of recycling center r for plant p.
$tpuf_n$	Recycling unit time of the finished product in a machine n in period t.
$tpuc_{c,n}$	Recycling unit time of the component c in a machine n in period t.
$NI_{n,r}$	Copies of a machine n originally existing at remanufacturing plant r.
$MaxNE'_{n,r,t}$	Maximum of machine n allowed to be added at remanufacturing plant r.
$CTRc_{c,r,p,t}$	Transportation mileage cost of returned component c/finished product p from remanufacturing plant r to production plant p in period t.
$CTKR_{k,r,t}$	Transportation mileage cost of the returned product from customer k to remanufacturing plant r in period t.
r_c	Maximum ratio allowed for recovering component c.
r_f	Maximum ratio allowed for recovering finished product.
$CSD_{d,t}$	Storage unit cost of the distribution center d in period t.

Parameter	Description
$CTK_{d,k,t}$	Transportation mileage cost from distribution center d to client k in period t.
$CF_{d,p}$	Fixed cost related to selection of distributor d for plant p in period t.
α_s	CO2 emission due to utilization of supplier s.
β_p	CO2 emission due to utilization of production plant p.
μ_d	CO2 emission due to utilization of distribution center d.
η_r	CO2 emission due to utilization of recycling center r.
EI_d	CO2 emission due to holding the product at distribution center d.
$EC_{s,p}$	CO2 emission due to transportation of components from supplier to plant p.
$EC_{p,d}$	CO2 emission due to transportation of products to distribution center d.
$EC_{d,k}$	CO2 emission due to transportation from distribution center d to client k.
$EC_{k,r}$	CO2 emission due to transportation of returned product from client k to recycling center r.
$EC_{r,p}$	CO2 emission due to transportation of remanufactured components and/or finished product from remanufacturing center r to plant p. [2pt]

4.3. Decision variables

Strategic level decision variables are mainly for the optimal selection of CLSC partners and are as follows:

- $S_{c,s,p,t} = \begin{cases} 1 & \text{if the supplier } s \text{ is selected to supply production plant } p \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$

- $P_{p,t} = \begin{cases} 1 & \text{if production plant } p \text{ is selected at time } t \\ 0 & \text{otherwise} \end{cases}$

- $D_{d,p,t} = \begin{cases} 1 & \text{if distribution center } d \text{ is allocated to production plant } p \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$

- $R_{r,p,t} = \begin{cases} 1 & \text{if remanufacturing center } r \text{ is selected at time } t \\ 0 & \text{otherwise} \end{cases}$

For tactical level, decision variables involve allocation of forward and reverse flows through the network. $Q_{c,s,p,t}$, $I_{c,p}$ and $QP_{p,t}$ are respectively the quantity of component c ordered from supplier s for plant p in period t, inventory of component at the plant p at the end of period t and quantity produced of finished product at plant p.

$QTD_{p,d,t}$, $QTK_{d,k,t}$ and $NSD_{d,t}$ are quantities of final product transferred respectively from producing plant p to distribution center d, quantity held in distribution center d and quantity of finished product transferred from distribution center d to customer k (forward flow).

$QT_{k,r,t}$, $QTRc_{c,r,p,t}$ and $QTRf_{r,p,t}$ are respectively quantity returned from client k to remanufacturing plant r, quantity of remanufactured component c and quantity of finished product transferred from remanufacturing plant r to producing plant p (reverse flow).

$NEA_{m,p,t}$, $NEA'_{n,r,t}$, $NES_{m,p,t}$ and $NES'_{n,r,t}$ are respectively number of copies added of machine m and n at production plant p and remanufacturing plant r and those removed from them.

4.4. Objective functions and constraints

The model proposed involves two objective functions: minimizing total CLSC costs (F1) and minimizing expected CO2 emissions (F2).

$$\begin{aligned}
F1 = &\sum_{t\in T}\sum_{c\in C}\sum_{s\in S}\sum_{p\in P}((CA_{c,s,t}+CT_{c,s,t})\cdot Dis_{s,p}\cdot Q_{c,s,p,t})\\
&+\sum_{t\in T}\sum_{c\in C}\sum_{s\in S}\sum_{p\in P} CF_{s,p,t}\cdot S_{c,s,p,t}+\sum_{t\in T}\sum_{c\in C}\sum_{p\in P} CS_c\cdot I_{c,p,t} \quad \textbf{(a)}\\
&+\sum_{t\in T}\sum_{m\in M}\sum_{p\in P}(Chp_{m,t}\cdot QP_{p,t}+CFA_{m,t}\cdot NEA_{m,p,t}+CFS_{m,t}\cdot NES_{m,p,t})\cdot P_{p,t} \quad \textbf{(b)}\\
&+\sum_{t\in T}\sum_{p\in P}\sum_{d\in D}(CTD_{p,d}\cdot Dis_{p,d}\cdot QTD_{p,d,t}+CF_{d,p}\cdot D_{d,p,t})\\
&+\sum_{t\in T}\sum_{d\in D} CSD_{d,t}\cdot NSD_{d,t}+\sum_{t\in T}\sum_{d\in D}\sum_{k\in K} CTK_{d,k,t}\cdot Dis_{d,k}\cdot QTK_{d,k,t} \quad \textbf{(c)}\\
&+\sum_{t\in T}\sum_{k\in K}\sum_{r\in R} CTKR_{k,r,t}\cdot Dis_{k,r}\cdot QT_{k,r,t} \quad \textbf{(d)}\\
&+\sum_{t\in T}\sum_{r\in R}\sum_{p\in P}(CTRc_{c,r,p,t}\cdot Dis_{r,p}\cdot QTRc_{c,r,p,t}+CTRf_{r,p,t}\cdot Dis_{r,p}\cdot QTRf_{r,p,t}+CF_{r,p}\cdot R_{r,p,t}) \quad \textbf{(e)}\\
&+\sum_{t\in T}\sum_{r\in R}\sum_{p\in P}(Chr_{r,t}\cdot QTRf_{r,p,t}+Chrc_{c,r,t}\cdot QTRc_{c,r,p,t})\\
&+\sum_{t\in T}\sum_{n\in N}\sum_{r\in R} CFRA_{n,t}\cdot NEA'_{n,r,t}+CFRS_{n,t}\cdot NES'_{n,r,t} \quad \textbf{(f)}
\end{aligned} \tag{1}$$

$$\begin{aligned}
F2 = &\sum_{t\in T}\sum_{c\in C}\sum_{s\in S}\sum_{p\in P}\alpha_s\cdot S_{c,s,p,t}+\sum_{t\in T}\sum_{p\in P}\beta_p\cdot P_{p,t}\\
&+\sum_{t\in T}\sum_{d\in D}\sum_{p\in P}\mu_d\cdot D_{d,p,t}+\sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\eta_r\cdot R_{r,p,t} \quad \textbf{(g)}\\
&+\sum_{t\in T}\sum_{s\in S}\sum_{p\in P} EC_{s,p,t}\cdot Dis_{s,p}\cdot S_{c,s,p,t}+\sum_{t\in T}\sum_{p\in P}\sum_{d\in D} EC_{p,d,t}\cdot Dis_{p,d}\cdot P_{p,t}\\
&+\sum_{t\in T}\sum_{d\in D}\sum_{k\in K} EC_{d,k,t}\cdot Dis_{d,k}\cdot D_{d,p,t}+\sum_{t\in T}\sum_{k\in K}\sum_{r\in R} EC_{k,r,t}\cdot Dis_{k,r}\cdot R_{r,p,t}\\
&+\sum_{t\in T}\sum_{r\in R}\sum_{p\in P} EC_{r,p,t}\cdot Dis_{r,p}\cdot R_{r,p,t} \quad \textbf{(h)}\\
&+\sum_{t\in T}\sum_{d\in D} EI_d\cdot NSD_{d,t} \quad \textbf{(i)}
\end{aligned} \tag{2}$$

The first part (a) of the economic objective F1 (Equation 1) consists of supply, transportation costs of components, Fixed costs paid to open new suppliers and components' holding costs at production plant. The second part (b) takes into account production, addition and removal of production machines costs. The third term (c) includes transportation costs from production plants to distribution centers, fixed costs paid to open distribution centers, finished products holding costs and transportation costs from distribution centers to customers. Transportation costs of returns from customers to remanufacturing plants are considered in the fourth term (d). Processing and transportation costs of remanufactured components and products are represented in terms (e) and (f) respectively.

The environmental objective F2 (Equation 2) contains three parts: the first part (g) involves carbon emission due to the utilization of suppliers, production and remanufacturing plants and distribution centers. The second part (h) represents carbon emission due to transportation between all facilities. The last part (i) consists of emission due to holding products at distribution centers. Considering the following constraints, the model is formalized as follows:

Minimize F1 and F2 under the following 19 constraints:

- **(c1)** $Q_{c,s,p,t} \leq \text{capmax}_{c,s,t} \cdot S_{c,s,p,t}$, $\forall c, s, p, t$
- **(c2)** $I_{c,p,t-1} + \sum_{s \in S} Q_{c,s,p,t} + \sum_{r \in R} QTRc_{c,r,p,t} \geq d_{c,p,t}$, $\forall c, p, t$
- **(c3)** $I_{c,p,t} = \sum_{s \in S} Q_{c,s,p,t} + \sum_{r \in R} QTRc_{c,r,p,t} + I_{c,p,t-1} - d_{c,p,t}$, $\forall c, s, r, t$
- **(c4)** $\sum_{r \in R} \sum_{p \in P} QTRf_{r,p,t} + \sum_{p \in P} QP_{p,t} \geq \sum_{k \in K} D_{k,t}$, $\forall t$
- **(c5)** $QP_{p,t} \cdot tpu_m \leq \text{Capprod}_{m,t} \cdot (NEI_{m,p} + NEA_{m,p,t} - NES_{m,p,t})$, $\forall m, p, t$
- **(c6)** $NEI_{m,p} + NEA_{m,p,t} - NES_{m,p,t} \leq \text{MaxNE}_{m,p,t}$, $\forall m, p, t$
- **(c7)** $\sum_{d \in D} QTK_{d,k,t} \geq D_{k,t}$, $\forall k, t$
- **(c8)** $NSD_{d,t} = NSD_{d,t-1} + \sum_{p \in P} QTD_{d,p,t} - \sum_{k \in K} QTK_{d,k,t}$, $\forall d, t$
- **(c9)** $QTRc_{c,r,p,t} \cdot tpuc_m + QTRf_{r,p,t} \cdot tpuf_m \leq \text{Caprecy}_{n,t} \cdot R_{r,p,t} \cdot (NI_{n,r} + NEA'_{n,r,t} - NES'_{n,r,t})$, $\forall n, r, t$
- **(c10)** $NI_{n,r} + NEA'_{n,r,t} - NES'_{n,r,t} \leq \text{MaxNE}'_{n,r,t}$, $\forall n, r, t$
- **(c11)** $\sum_{k \in K} \sum_{r \in R} QT_{k,r,t} \leq \sum_{p \in P} QP_{p,t}$
- **(c12)** $\sum_{k \in K} \sum_{r \in R} QT_{k,r,t} \cdot r_c \leq \sum_{p \in P} QTRc_{c,r,p,t}$, $\forall t$
- **(c13)** $\sum_{k \in K} \sum_{r \in R} QT_{k,r,t} \cdot r_f \leq \sum_{p \in P} QTRf_{r,p,t}$, $\forall t$
- **(c14)** $F2 \leq \text{maxC}$, $\forall t$
- **(c15)** $Q_{c,s,p,t}, I_{c,p} \geq 0$
- **(c16)** $QP_{p,t}, QTD_{d,p,t}, QTK_{d,k,t}, NSD_{d,t} \geq 0$

- **(c17)** $QT_{k,r,t}, QTRc_{c,r,p,t}, QTRf_{r,p,t} \geq 0$
- **(c18)** $NEA_{m,p,t}, NES_{m,p,t}, NEA'_{n,r,t}, NES'_{n,r,t} \in \mathbb{N}$
- **(c19)** $Z_{c,s,p,t}, P_{s,t}, D_{d,p,t}, R_{r,p,t} \in \{0,1\}$

Constraint (c1) shows that purchased quantity of the component c is limited by the production capacity of its supplier s. This is valid for each component at any planning period. Constraint (c2) is for components demand satisfaction. It shows that the sum of amounts of a component received from all suppliers and those recovered from all remanufacturing plant in a period added to inventory of the previous period must meet the forecasted demand for this component at plant p in this period. Constraint (c3) shows that inventory for a component in the end of period (t) at plant p is a function of quantity in stock at the end of the previous period (t-1), purchased and recovered quantities minus the expected demand for period (t). Constraint (c4) is for finished product demand satisfaction. It ensures that quantities produced at all plants and those recovered must meet its estimated demand for each period. Constraint (c5) ensures that quantities produced of finished product at a plant p respect production capacity of all available machines in each period at this plant. Constraint (c6) limits number of machines implemented. Constraint (c7) responds to customer demand satisfaction. It shows that quantities of finished product delivered from all distribution centers should meet customer demand. Constraint (c8) reflects the flow conservation at distribution centers. they must receive enough finished product from production plant in order to meet all demands. Constraint (c9) respects capacities of remanufacturing plants. It shows that components and finished products ‘quantities that have been recovered at remanufacturing plant respect their available machines capacities. Constraint (c10) is for the limitation of remanufacturing machines implementation. Constraint (c11) guarantee that forward channel is greater than reverse one. Constraints (c12) and (c13) respect returned product ratios. Constraint (c14) is for respecting the carbon policy. It shows that the amount of carbon being emitted across the CLCS network mustn’t exceed the CO2 emission allowed by legal restrictions. Non negativity and binary constraints are presented in constraints (c15) to (c19).

5. Experimentation

Before presenting numerical experiments, the metaheuristic solution method adopted with its different parameters, namely, chromosome representation, fitness evaluation and genetic operators are presented in the following subsections. The ”*gamultiobj*” solver in MATLAB is employed to solve our MILP. It is designed specifically to address such problems using genetic algorithms, which are inspired by the process of natural selection, to search for a set of Pareto optimal solutions. The solver iterates through generations of solutions, using operators such as selection, crossover, and mutation to evolve the population towards optimality.

5.1. NSGA-II solution method

The non-dominated sorting genetic algorithm NSGA-II method was firstly introduced by (Deb et al., 2002). It maintains the convergence and diversity of the Pareto set by using non-dominated sorting and crowding distance measure, respectively [35]. The Pareto front represents a set of non-dominated solutions where no single objective can be improved without degrading another. In the context of bi-objective optimization, the Pareto Front provides a visual and analytical representation of the trade-offs between the two objectives. Each point on the Pareto Front signifies a solution where improving one objective would necessitate a compromise in the other.

The optimization process using `gamultiobj` involves several key steps:

i. **Initialization**: A population of candidate solutions is randomly generated.

ii. **Evaluation**: Each solution is evaluated based on the defined objective functions.

iii. **Selection**: Solutions are selected for reproduction based on their dominance status. Non-dominated solutions are preferred, contributing to the formation of the next generation.

iv. **Crossover and Mutation**: Genetic operators are applied to create new solutions. Crossover combines parts of two solutions, while mutation introduces random variations.

v. **Pareto Front Update**: After each generation, the solutions are evaluated, and the Pareto Front is updated to include new non-dominated solutions while discarding dominated ones.

vi. **Convergence**: This process repeats until a stopping criterion is met, such as a maximum number of generations or convergence to a stable Pareto Front.

Next subsections adapt the NSGA-II to our problem.

5.1.1. Chromosome representation The encoding of the problem to be solved into a chromosome is an essential part of any GA implementation. Optimization in our problem consists on seeking optimal set of CLSC partners with allocation of forward and reverse flows. Therefore, a chromosome represents a model solution where each gene corresponds to a decision variable.

5.1.2. Fitness function and selection method NSGA evaluates chromosomes based on fitness function value. Since we aim to minimize the overall costs and carbon emissions, the smaller fitness value is the better. In this work, fitness function is the two objective functions with the corresponding constraints. According to NSGA-II requirements, the tournament selection technique is used in this work.

5.1.3. Tuning GA parameters To enhance optimization performance and solution quality, tuning the parameters of the genetic algorithm is crucial. This task is complex due to the non-trivial interactions among the parameters. In this study, we adopted a step-by-step approach. First, we identified the key parameters: population size, crossover rate, mutation function, and Max Generation (stopping criteria). We then proceeded with progressive tuning by modifying one parameter at a time to understand its individual impact on the algorithm's performance. For each parameter, we selected a reasonable range of values to test. After each adjustment, we conducted a visual evaluation to determine the best value to set for the parameter in question. This evaluation was based on selecting the Pareto Front that best approached both axes simultaneously, indicating an optimal balance between the objectives.

5.2. Numerical experiments data

To test our model, we consider a CLSC network consisting of two components suppliers, one production plant, two distribution centers, two remanufacturing plants and two customers. The product plant has 3 machines (1 machine type M1 and 2 machines type M2). Remanufacturing plants have 2 types of machines N1 and N2. We studied a finished product assembled from two components C1 and C2. Parameters setting are illustrated in Table 3.

Table 3. Parameters setting of the numerical experiment

Parameter	**Notation**	**Value**
Components' costs	$CA_{c,s,t}$	7,6,5,7
	$CT_{c,s,t}$	5,6
	$CS_{c,p}$	3,4
Production/remanufacturing costs	$Chp_{m,t}$	3,1
	$Chr_{n,t}$, $Chrc_{c,n,t}$	5,6
	$CSD_{d,t}$	3,4
Fixed costs	$CFA_{m,t}$, $CFR_{m,t}$	90,100,40,50
	$CFRA_{n,t}$, $CFRS_{n,t}$	100,90,40,30
Transportation costs	$CTD_{p,d,t}$	8,9
	$CTK_{d,k,t}$	9,8
	$CTKR_{k,r,t}$	7,6
	$CTRc_{c,r,p,t}$, $CTRf_{r,p,t}$	5,6
CO2 released by facilities	α_s , β_p , μ_d, η_r	3,4,5,2,2,2,3
	EI_d	8,9
CO2 emission due to transportation	$EC_{s,p}$	0.3,0.4
	$EC_{p,d}$	0.2,0.2
	$EC_{d,k}$	0.2,0.1,0.1,0.2
	$EC_{k,r}$	0.3,0.2,0.1,0.3
	$EC_{r,p}$	0.2,0.1
Distance between facilities	$Dis_{s,p}$, $Dis_{p,d}$	10,70,50,20
	$Dis_{d,k}$	120,80,60,100
	$Dis_{k,r}$, $Dis_{r,p}$	70,90,120,100,20,30
Demand	$d_{c,p,t}$	160,160
	$D_{k,t}$	90,70
Capacities	$Capmax_{s,c,t}$	100,160,120,140
	$Caprod_{m,t}$, $Caprecy_{n,t}$	300,200,100,200
	$MaxNE_{m,p,t}$, $MaxNE'_{n,r,t}$	8,10,6,5
Return ratios	r_c, r_f	0.1,0.15,0.3

5.3. Computational results

As mentioned before, we proceeded with progressive tuning of GA parameters by modifying one parameter at once to highlight its individual impact on algorithm performance and Pareto front solution. Next subsections show the computational results according to tuning of the following GA parameters: *population size*, *crossover rate*, *mutation function*, and *Max Generation* (stopping criteria).

5.3.1. Population size impact We tested the following values for population size: 100, 200, 300 and 400. Results depicted in figures (2, 3, 4 and 5) show that the more population size is great, the more values of overall costs F1 (objective 1) and CO2 expected emission F2 (objective 2) are minimal. This is true for population size from 100 up to 300.

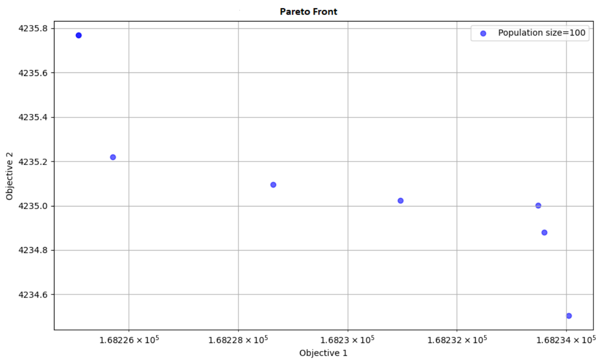

Figure 2. Pareto front for population size 100.

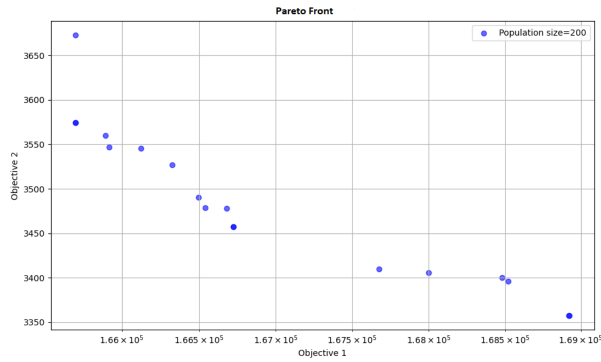

Figure 3. Pareto front for population size 200.

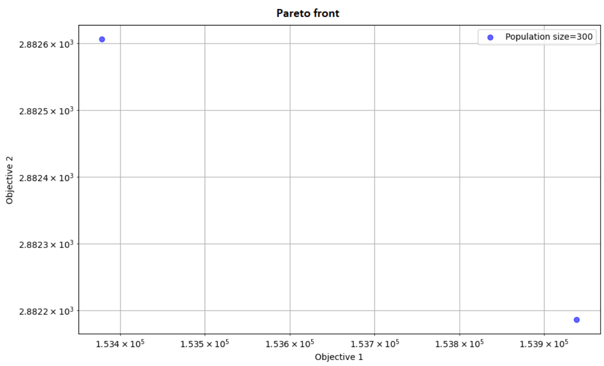

Figure 4. Pareto front for population size 300

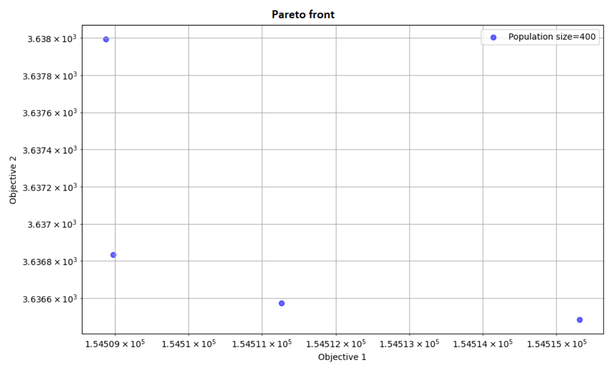

Figure 5. Pareto front for population size 400

As shown in figure 5 , the performance starts to degrade at population size 400 in which the first objective is ranged from $1.54509{\times}10^5$ to $1.54515{\times}10^5$ after being ranged from $1.534{\times}10^5$ to $1.539{\times}10^5$ for population size 300. The same remark is observed for the second objective which is ranged from $3.636{\times}10^3$ to $3.368{\times}10^3$ after being ranged from $2.8822{\times}10^3$ to $2.8826{\times}10^3$ for population size 300.

Comparing the four figures, population size 300 is the best value that gave a good Pareto front. This value is kept then as optimal one for next simulations.

5.3.2. Maximum generation impact Now, we set the population size to 300 and we vary the value of the maximum number of generations as a stopping criterion for the genetic algorithm. We tested the following values: 20, 50, 100, 200, 300 and 400. Simulation results are depicted in figures (6, 7, 8, 9, 10 and 11). The Pareto front improves up to 300 where it begins to deteriorate for 400 as maximum number of generations. The good value is therefore equal to 300.

5.3.3. Crossover rate impact We fixed optimized values of the previous parameters (population size=300, max generation =300) and we vary the value of crossover rate. The crossover operator means that two

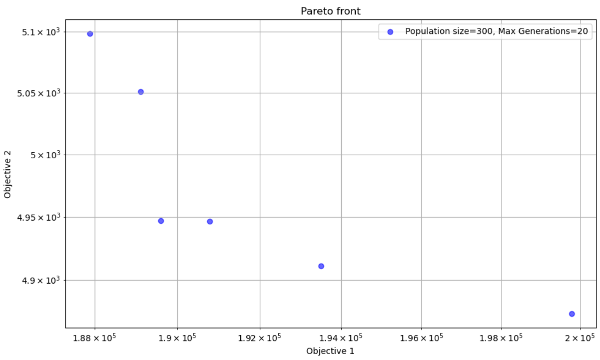

Figure 6. Pareto front for number of generations 20.

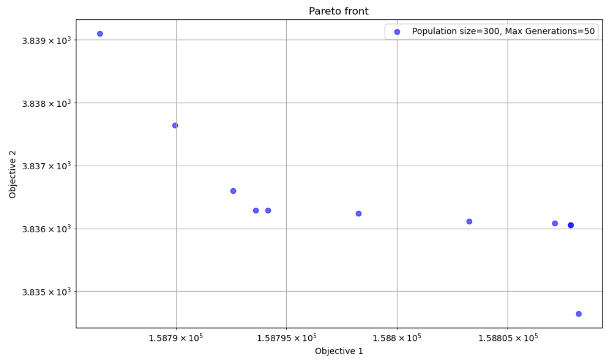

Figure 7. Pareto front for number of generations 50.

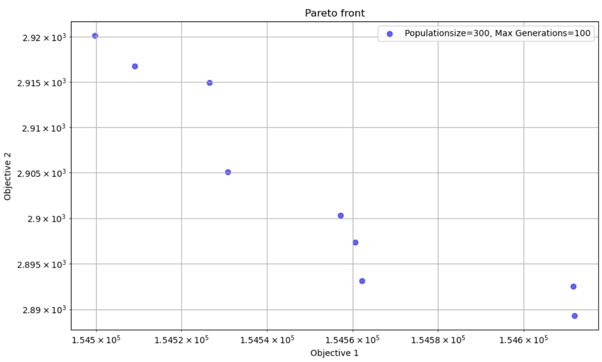

Figure 8. Pareto front for number of generations 100.

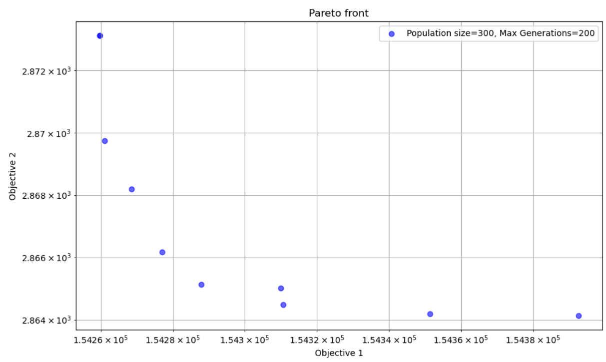

Figure 9. Pareto front for number of generations 200.

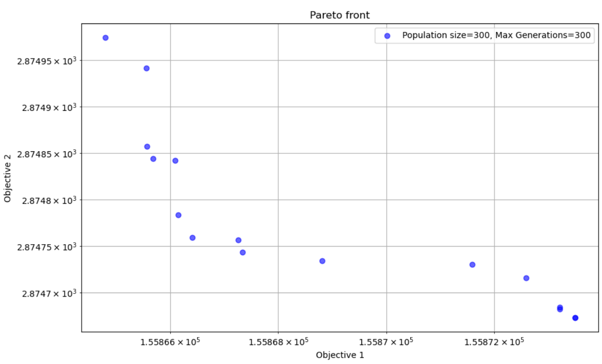

Figure 10. Pareto front for number of generations 300.

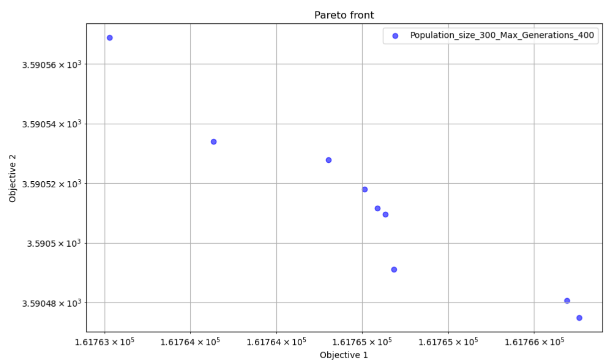

Figure 11. Pareto front for number of generations 400.

parent chromosomes are randomly chosen to exchange part of their genes with a certain probability or rate. We experiment the following values of crossover rate : 0.6, 0.7, 0.8, and 0.9. Pareto solutions obtained are illustrated in figures (12, 13, 14 and 15).

Comparing these results, the Pareto front that best optimized the two objective is that provided by crossover rate 0.8.

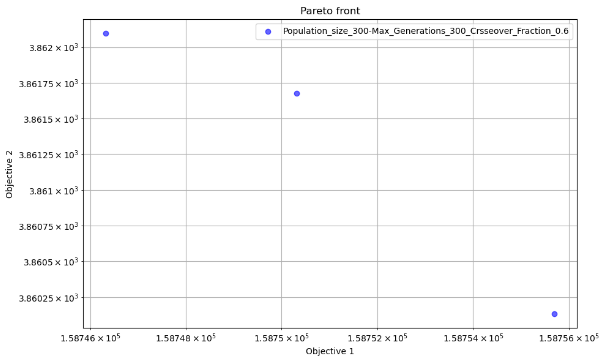

Figure 12. Pareto front for crossover rate 0.6

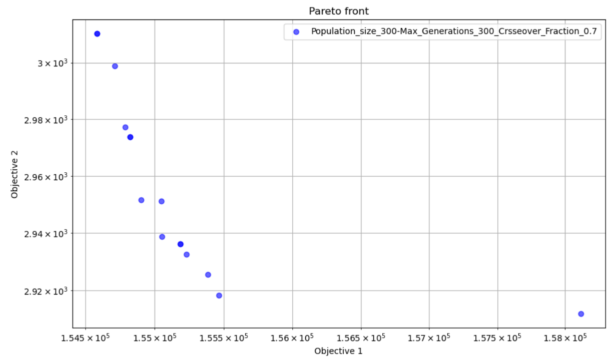

Figure 13. Pareto front for crossover rate 0.7

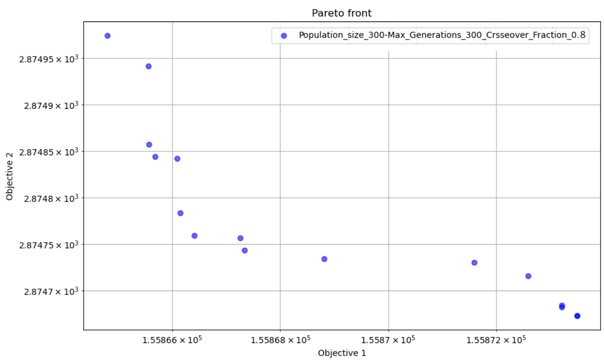

Figure 14. Pareto front for crossover rate 0.8

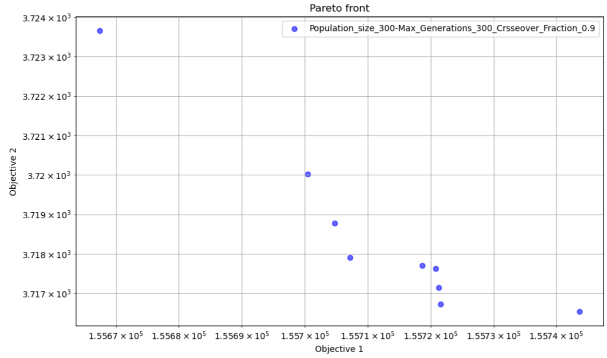

Figure 15. Pareto front for crossover rate 0.9

5.3.4. Mutation impact the same logic is conducted for mutation type. We kept population size at 300, maximum number of generations at 300 and crossover rate at 0.8 and we varied the mutation type. The Matlab gamultiobj solver gives the possibility of choosing between several types of mutation: Mutationgaussian, Mutationadaptfeasible, MutationPower, mutationpositivebasis and MutationUniform.

The *mutationgaussian* function adds a random value from a normal distribution, suitable for continuous variables requiring small adjustments. The *mutationpositivebasis* function uses a positive basis to systematically explore positive directions in the solution space, particularly useful for balanced exploration (figures 16 and 17).

The *mutationadaptfeasible* function adapts mutations to remain within limits and satisfy problem constraints, ideal for complex non-linear constraints. The *mutationpower* function applies a mutation based on a power distribution, modifying individual elements according to a power parameter, ideal for non-linear changes (figures 18 and 19).

Finally, the *mutationuniform* function replaces elements with uniformly distributed values, useful when variables can take any value within a defined range. These functions increase the diversity of solutions and enhance the chances of finding optimal solutions (figure 20) .

Comparing these results, the *mutationpower* provides then the best Pareto front obtained with all optimized GA operators.

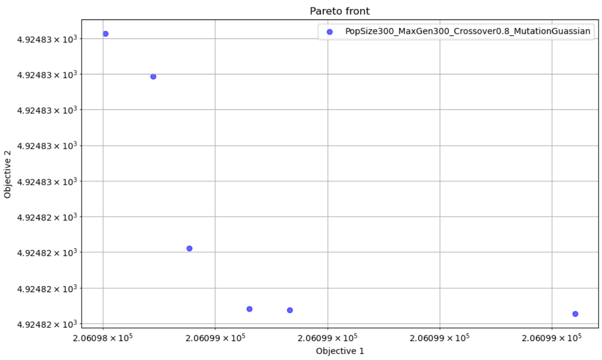

Figure 16. Pareto front for Mutationgaussian

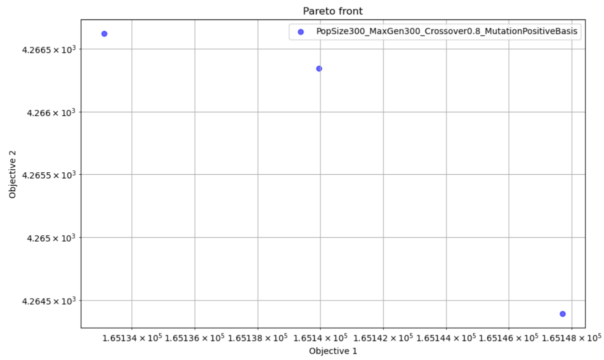

Figure 17. Pareto front for Mutationpositivebasis

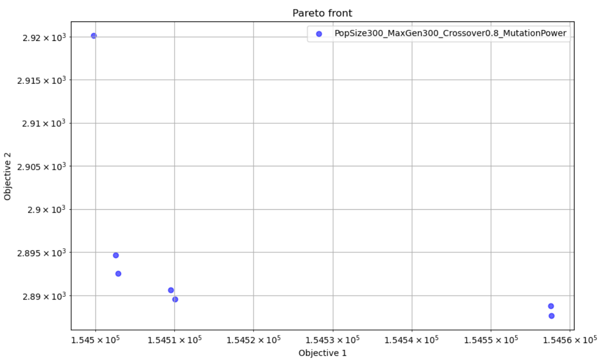

Figure 18. Pareto front for Mutationpower

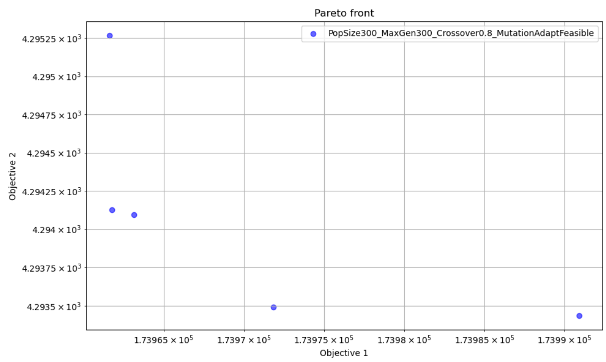

Figure 19. Pareto front for Mutationadaptfeasible

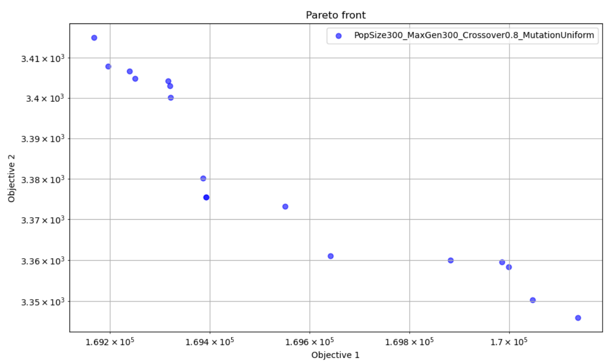

Figure 20. Pareto front for MutationUniform

Table 4. Impact of deviation in input model parameters

Change in % in parameter value	**-50**	**-20**	**+20**	**+50**
Demand effect				
Objective 1 (F1)	-48.13%	-13.28%	+20.68%	+59.06%

Change in % in parameter value	-50	-20	+20	+50
Objective 2 (F2)	-44.06%	-10.49%	+32.96%	+88.61%
Costs effect				
Objective 1 (F1)	-51.69%	-25.37%	+16.75%	+42.28%
Objective 2 (F2)	-1.44%	-3.26%	-3.75%	-2.12%
Distance effect				
Objective 1 (F1)	-48.42%	-21.78%	+18.74%	+41.77%
Objective 2 (F2)	-2.52%	-1.18%	+1.05%	+5.45%

5.4. Sensitivity analysis

The aim of this section is to conduct a sensitive analysis of input parameters having practical impact on the optimal problem solution for our model. We studied the impact of the deviation in the following parameters: demand, costs and distance between facilities. We explored then how the total CLSC cost (F1) and CO2 emission (F2) changed with these deviations. Results of the corresponding computations are presented in Table 4.

The sensitivity analysis conducted for demand change shows that as far as demand increases (respectively decreases) the total cost and the total emission increase (respectively decrease). This could be explained by the fact that demand increase enhances the need for more amounts of products to be supplied, produced and transported which leads to the overall cost increase and that of total emission as well. This proportionality is also true when the demand decreases.

The same observation is noted for change in distance between facilities and for costs change for the first objective. For the second objective, the linearity is not observed since total emission is affected mainly by facilities activity and distances traveled rather than costs.

To sum up, for the three parameters changes, the two objective functions change proportionally. This is logic since the objective functions and all constraints are linear in the model proposed.

5.5. Comparative analysis with weighted sum method

The weighted sum method aims to convert the multi-objective problem to a single objective one by assigning different weights to the objective functions. In general, Weights values are attributed by decisions makers according to their expertise. In our bi-objective optimization problem case, there are two weights ($w1$ and $w2$) to be assigned to objective function F1 and F2 respectively. It is noticeable that $w_1, w_2 \geq 0$ and $w_1 + w_2 = 1$. Therefore, the weighted sum formula adapted to our case is as follows:

$$\begin{cases} \text{Min } \{F = w_1 \cdot F_1 + w_2 \cdot F_2\} \\ \text{Subject to constraints (c1) to (c19)} \end{cases} \tag{3}$$

Table 5. Weighted sum method results

Weights configuration	Objective (F)	Objective (F1)	Objective (F2)
$(w_1 = 0.75; w_2 = 0.25)$	143191	189010	5735

Weights configuration	Objective (F)	Objective (F1)	Objective (F2)
$(w_1 = 0.65; w_2 = 0.35)$	122009	184900	5210
$(w_1 = 0.6; w_2 = 0.4)$	110836	182400	3490
$(w_1 = 0.4; w_2 = 0.6)$	70322	167960	5230
$(w_1 = 0.8; w_2 = 0.2)$	90190	111590	4590

The problem has been programmed and resolved using the MATLAB GA optimtool. The model was run for different values of $w1$ and $w2$ (see Table 5). For each weights' configuration, values of the two objective functions F1 and F2 are calculated based on decision variables values given by the solution and registered in order to be compared to values obtained using the NSGA-II method. As illustrated in Table 5, assigning values to weights w1 and w2 gives us an idea of the solution for a single and particular situation. Therefore, we must run a very large number of the two weights combinations to test different possible scenarios. In fact, the weighted sum method allows only to approach the Pareto front but does not allow falling on the exact points that constitute it.

By comparing these results with those obtained from NSGA-II, we conclude that NSGA-II surpassed the weighted sum method in terms of performance, ease of use, and effectiveness of the solutions. Evaluating the Objective F1 and F2 values for both methods, the weighted sum method still falls short of the Pareto front values achieved by the NSGA-II algorithm (Objective F1 ranged from 154500 to 154560 and objective F2 ranged from 2890 to 2920). This method requires running the maximum number of possible weight configurations.

This comparative example clearly shows the good performance of the NSGA-II genetic algorithm for solving the bi-objective problem.

6. Conclusion and future scope

In this paper, we attempt to provide a four-echelons CLSC network design model integrating forward and reverse flows. The main objective of the model is to seek an optimal selection of facilities, namely suppliers, production plants, distribution centers, and remanufacturing plants, as well as optimal product flows and machine allocation in both direct and reverse channels.

Given that decision makers need to assess the trade-off between costs and environmental impact within a CLSC system, we have implemented a bi-objective optimization. The first objective function seeks to minimize costs associated with supply, transportation, remanufacturing, and storage of components. Additionally, it aims to reduce costs related to the production, remanufacturing, and transportation of returned products, as well as the costs of adding or removing production and remanufacturing machinery. The second objective function focuses on minimizing CO_2 emissions arising from the use of CLSC facilities and the transportation between them.

To solve the bi-objective problem, the NSGA-II multi-criteria genetic algorithm was adopted. It contributes to generate a set of Pareto-optimal solutions that best meet both optimization criteria. Since GA operators have a significant impact on their performance, we have investigated, through computational experiments, the impact of each operator on the fitness functions in order to determine the optimal combination of these parameters that offers the best Pareto front solutions. In addition to the numerical experiment, the effectiveness of the suggested model is illustrated through a sensitive analysis in which the impact of the deviation of significant input parameters on the two objectives was investigated. This analysis showed how much the model proposed is adapted to tackle sources of supply chain flexibility, such as demand variability through different product life cycles, costs changes, and facilities location.

Several extensions are worthy of analysis. For example, this paper does not consider uncertainties such as stochastic demand, it would be interesting to develop in further work a fuzzy multi-criteria decision-making model with advanced stochastic programming algorithms to handle more realistic scenarios. Another possible application of our research is to include in our model constraints on the quality of returned components and products to ensure that returns could be integrated to the forward channel without any quality concerns. Another extension to pursue is to consider other important emissions such as NO2 and SO2 for the facilities and transportation network. For all these possibilities, future research directions would explore other advanced optimization techniques.

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