



Facility disruptions in a closed-loop supply chain featuring warranty policy and quality-based segmentation of returns

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Abstract. This paper focuses on a closed-loop supply chain that deals with disruptions at distribution centers and optimizes the network in two dimensions of sustainability: economic and environmental. Avenues for cost minimization are designed for the customer by adding warranty periods, reworking options, and incentives for returning the used items. Non-dominated solutions via the *Reservation Level-driven Tchebycheff* procedure are found by appropriate choice of facility establishment and suitable allocation links considering the disruption at the distribution centers. The concept of primary and supporting allocations is introduced to address the disruptions and ensures an uninterrupted flow of service. Environmentally, the model adopts a zero-waste strategy by embedding various return-segmentation policies and a secondary chain. The backward flow depends on customers' choice of reworking, validity of the warranty contract, and quality of the returns. The test results indicate that manufacturing and distribution centers prefer returns with medium-range quality, while due to the incentives offered for recyclable items, customers benefit the most from returning the items with the lowest quality. The tests on the probability of disruptions indicate that establishing a minimum number of manufacturing and/or distribution sites without disruption leads to better overall performance.

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1. Introduction

A Closed-Loop Supply Chain Network (CLSCN) imitates the working of a dynamic, complex, and large-scale system with forward and reverse flows. In a CLSCN, various decisions are necessary to ensure an acceptable outcome, and the more complex a network, the greater the uncertainty level of the decision-making [1]. The rationale for handling uncertainties in a CLSCN revolves around the optimization of one

or more sustainability dimensions: economic, social, and environmental aspects [2]. In a CLSCN, uncertain scenarios can be typically classified into two main categories [3]:

(a) Uncertainties are linked to strategic decision-making, e.g., finding optimum production capacity, placement of facilities, customer allocation, supplier selection, node-to-node links in the network, segmentation policies in the backward flow, and transportation at different levels of the Supply Chain (SC);

(b) Uncertainties are taken into account while calculating the reliability or robustness of the network to handle the imprecision or inexactness of information (e.g., due to dynamism and fluctuation in demands, capacities, and timings), potential vulnerability and

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risks (e.g., due to globalization or leanness), and disruptions (e.g., due to random incidents, natural disasters, political tensions, epidemic outbreaks, and terrorist attacks).

The present study relates to both categories in which: (a) the establishment of the facilities and the customer allocation are uncertain; (b) disruptions may occur at Distribution Centers (DCs), hindering the service to the customers; and (c) the flow of the returned items in the backward chain depends on the warranty agreement and the quality-based segmentation policies. The novel contributions of this paper are listed as follows:

1. Instead of the usual approach to maximizing the chain profit prior to sending out the product and excluding the customer benefits, the proposed CLSCN recognizes customer as an integral part of the chain and includes the customer's profit in the optimization model;
2. As a proactive approach, in order to increase the reliability of the CLSCN, the model determines the location of the DCs and their corresponding customer allocation, both for the primary and supporting DCs, simultaneously. Hence, following the occurrence of disruptions, two sets of allocation decisions are available to the decision-maker. Moreover, the supporting allocation is always directed to the DCs without disruptions to ensure constant availability of service;
3. In the backward flow, the returns are handled based on the customers' preference, warranty validation, and the quality of used items as follows:
 - (a) If the warranty period is still valid, the product is first collected by the DCs, sent back to the manufacturer for remanufacturing, and finally returned to the customer free of charge;
 - (b) If the warranty period is ended, three scenarios may occur:
 - (i) The damage to the item is minimal; thus, the customer may prefer to personally take the product to a nearby shop for a quick repair, forgoing the time and cost of returning the product to the chain (i.e., reworking by the customer);
 - (ii) The product is fairly damaged; thus, the customer returns the product to the DCs for repair;
 - (iii) The returned product by the customer (for an incentive) is unusable in its current form; thus, it is sent out through the DCs to a secondary chain to be salvaged for parts.

The idea is to maximize the overall profit while maintaining the sustainability and reliability of the chain by creating a zero-waste network, which is functional even in case of disruptions.

The related literature is classified into three parts: papers on the CLSC focusing on the sustainability of the chain, research regarding the facility location in the CLSC, and the articles featuring CLSC with the possibility of disruption across facilities.

1.1. Sustainability in the CLSCN

In recent decades, extensive research has been carried out on the CLSC in response to increased awareness regarding the environmental issues in order to preserve the finite natural sources, increase profit, and improve the social welfare. For instance, Govindan and Soleimani [4] conducted comprehensive research on a CLSC using a secondary supply chain as a recycling outlet for the used items. The additional chain creates a passive income by selling recycled items, thus increasing the overall profit of the chain.

The environmental issues in a bi-level CLSCN including manufacturers and the retailers were addressed in [5]. In the paper, three sustainability factors regarding the environment were considered: (a) the materials used in the (re)production activities, (b) the greenhouse gas emissions resulting from the production and transportation activities, and (c) the materials used for reproduction (recycling).

Maiti and Giri employed game theory to review the recovery policies [6]. Their division policy was based on the pre-determined minimum quality calculated from the cost of reconstruction. Thus, if the returned product is of higher quality than the minimum required quality, it will be sent for reconstruction; otherwise, it will be sold in the secondary market.

Xu et al. proposed a CLSC to tackle the issue of carbon emission [7]. Their CLSC has extended recovery options, providing independent facilities for collecting, sorting/testing, reconstruction, repair, redistribution, recycling, and disposal of used products. However, similar to the previous research, the number of products entering these facilities is partially pre-determined.

Masoudipour et al. proposed a CLSCN in the textile industry, where the returned products are collected through DCs and divided in terms of quality [8]. In the reverse chain, the returned products are divided into three categories: products that require simple repairing, products that must be returned to the factory for reproduction operations, and finally recyclable products, which should be sent to the secondary chain. Moreover, a bi-objective, mixed integer programming model is used to maximize the profits of the manufacturers and DCs. Similar to their study, in our present model, the policy of classification and separation of the returned products is considered in terms of product quality and modeling is based on maximizing the profitability of the entire supply chain.

Zhen et al. presented an integrated landscape for developing a green and sustainable ring of supply chain

network under uncertain demand [9]. A two-objective optimization model is proposed to reduce CO₂ emission and the total operating costs. The returned products from the customers are considered repairable.

1.2. Facility location in CLSC

Yi et al. designed a retail-oriented CLSC network to reproduce the end-of-life construction machinery while investigating the location of the facilities [10]. The designed network is tackled by a genetic-algorithm-based exploration method.

Ahmadzadeh and Vahdani integrated decision-making strategies into the location, inventory, and pricing of a closed-loop network considering customer demands [11]. Their solution approach involves two encryption and decryption methods to solve the CLSC.

Mirmohammadi and Sahraeian designed the distribution network including determining the number and location of the facilities, allocating customers to the network, and determining the transport of different goods from different origins to destinations in the distribution network [12]. Returned products in the reverse chain were divided into four categories in terms of quality: repairable, recyclable, disposable, and renewable (to be sold in the secondary chain).

Yu and Solvang developed a new multi-objective, fuzzy-random mathematical model to design a stable CLSC network [13]. This model is developed to make a trade-off between cost efficiency and environmental performance in different types of uncertainty. The environmental performance of the network is measured by considering the amount of carbon emission. Decisions are made to locate the facilities.

Govindan et al. proposed a combined approach including the fuzzy analysis of networking process and mixed integer linear multi-objective programming models [14]. Furthermore, the selection of a circular source and allocation of orders in the CLSC led to the development of several products with regard to the issue of green routing and usage of heterogeneous vehicles. Consequently, a mathematical model was developed for a routing-inventory-location problem to minimize the cost and scarcity in an uncertain environment.

1.3. Probability of disruption in CLSC

In the related literature, the term *disruption* mostly indicates random uncertainty and it basically occurs out of the norm, which negatively impacts the chain.

For instance, researchers study an environmentally sustainable CLSCN, where *demand disruptions* occur at the supplier level and the resultant effect reverberates throughout the chain, impacting the retailer's action and delivery times [15]. The *uncertain* variables of the chain are considered as fuzzy numbers and

tackled by the combination of Karush-Kuhn-Tucker (KKT) conditions and possibility theory.

Similarly, Diabat and others designed a reliable SC network with perishable products considering disruptions [16]. *Disruption*, in this case, is defined as *disaster scenarios*, in which case the proposed model attempts to minimize the time and cost of the network by utilizing the Lagrangian relaxation and ϵ -constraint approaches.

Moreover, the effect of production disruption in an economic and environmentally sustainable SC was studied [17]. In terms of economy, their three-echelon, Stackelberg game model maximizes the profit by determining the best pricing, inventory, and maintenance strategies. As for the environmental dimension, the aforementioned model considers the effect of carbon dioxide emission on the SC network.

Also, Tong et al. focused on a sustainable CLSC minimizing the cost related to supply disruption and carbon tax [18]. The problem was tackled by meta-heuristics, and the effects of different policies pertaining to the uncertain parameters on the optimal production and recycling strategies were investigated.

The study by Darom et al. is similar to the present paper since a predictive approach is defined in the SC to counter the potential supply disruptions [19]. They used the concept of *safety stock* in a two-level, manufacturer-retailer chain to lower the disruption cost and carbon emission in the recovery mode.

In addition, Shen focused on a sustainable SC considering the environmental impact of carbon dioxide emissions and the social benefits of increasing employment opportunities [20]. The demand, cost, and capacity in this problem are uncertain; hence, the model is solved via the chance-constrained method.

Similarly, Mohammadi utilized chance constrained programming to tackle the problem of supplier selection with uncertain demands in a hazardous material SC network [21].

Furthermore, the total cost was minimized in a reliable SC considering the demand uncertainty and facility disruption [3]. The problem was formulated as a stochastic mixed-integer model and solved via the L-shaped decomposition method.

Based on the reviewed literature, it is apparent that the choice of the solution approach mainly depends on the specifications of the problem and the nature of the uncertainty. The review paper by Tordecilla [1] states that hybrid simulation-optimization methods are the most common way of optimizing uncertain SC networks. The simulation side handles the uncertainty, while the optimization side achieves (near) optimal solutions. Discrete-event simulation and mixed-integer linear programming are mentioned as the two of the most used approaches of simulation and optimization methods, respectively.

The present study utilizes discrete-event scenarios and optimization modeling, in which based on the probability of disruption, the network either functions with the primary DC (with disruption) or switches to a supporting DC (without disruption) to ensure a reliable chain. The optimization model factors in the best placement of the facilities and the forward and backward routings of the products via an interactive multi-objective decision-making technique known as the Reservation Level-driven Tchebycheff Procedure (RLTP).

The rest of this paper is organized as follows. Section 2 formulates the proposed CLSCN as a mixed-integer model. Section 3 presents the proposed solution approach for the multi-objective model. Section 4 shows the applicability and suitability of the solution approach on the model via a numerical example. Section 5 examines the relationships between the quality of returns and the probability of disruptions on the objective values. Finally, the managerial insights and conclusion are given in Sections 6 and 7, respectively, and the promising research on the subject is suggested.

2. Methodology

The proposed CLSCN in the current paper is based on the model by Masoudipour et al. [8], and the interested reader is referred to the corresponding paper for more details. The improved version of the model is depicted in Figure 1 and can be explained as follows:

- The *forward* flow consists of three stages: the manufacturing facilities, the DCs with (out) the

possibility of disruptions, and the customers. The optimization model decides on facility establishment for manufacturing and DCs. Two types of allocations are calculated per customer: primary and supporting. Primary allocations can be directed at DCs with or without disruptions. Supporting allocations, however, are only assigned to DCs without disruptions to ensure a resilient structure. It should be noted that *disruption* is seen as a feature for the DCs and thus, a DC can be established such that it may be unavailable at times (with disruption), or so fully equipped that it is always available (without disruptions). Since establishing the latter costs more than the former, the model balances out this choice by weighing the benefits of reducing establishment costs versus a constant flow of service;

- In the *backward* flow, customers have the option of reworking the products themselves without shipping them back to the chain in order to save time and/or cost of a return process. Otherwise, they can send the products back to the DCs. Once the DCs collect the products, the warranty validation is checked. If the damage is covered under a valid warranty, the product is sent to the manufacturer to be fixed and the remanufactured product is sent back to the customer. If the warranty is void, but the quality of the item meets the repairing specifications, then the DC undertakes the repairing of the used item and the cost of the process is inflicted upon the customer. If the product is beyond salvation, the DCs buy back the product from the customers so as

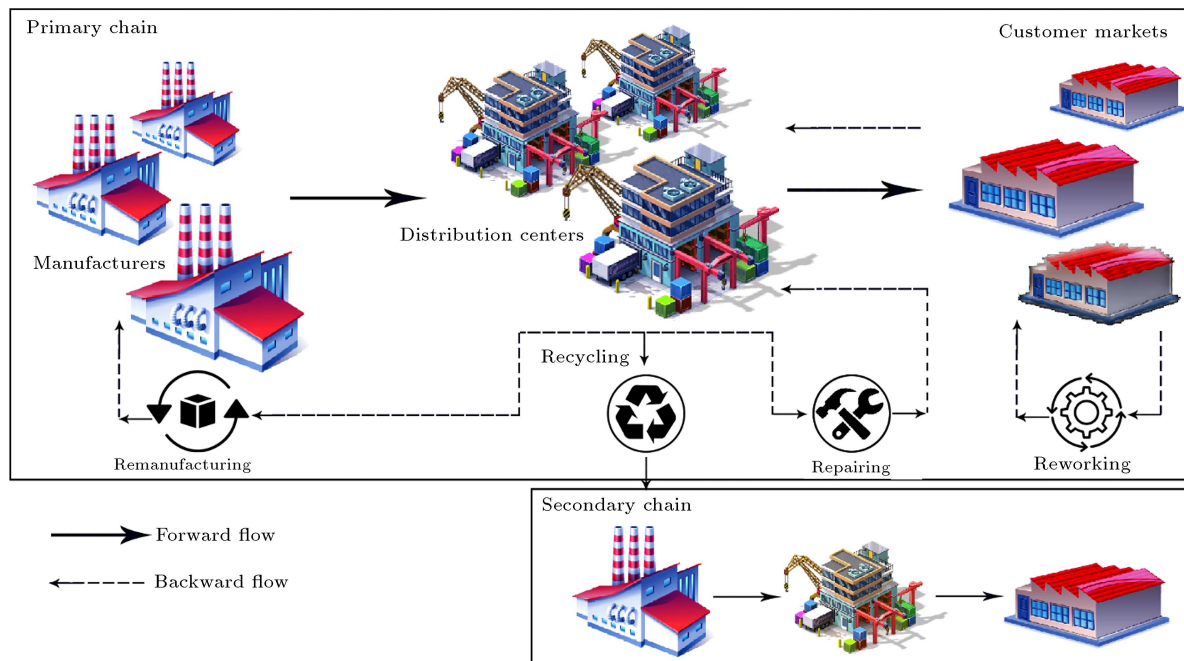


Figure 1. An overview of the proposed CLSCN.

to avoid environmental violations and sell it out as raw materials to a secondary chain;

– An example of such a CLSCN can be found in the supplying process of spare parts for the plants and machines across various industries (e.g., automotive spare parts, excavation, farming or earthworks machinery parts, hot-cast mechanical components and molds, and the machinery parts involved in textile, pneumatic, electromechanical, electronic, healthcare, and medical industries). These parts often have extended warranty coverage, and the manufacturers encourage customers to return the end-of-life products to either avoid environmental violations/fines or sell the recyclable returns (mostly consist of metal or plastic) to another chain. The quality measure of returns differs across various industries, and mainly includes the component's efficiency, compressive strength, wear rate, and depreciation [22].

The assumptions, notation, and mixed-integer mathematical formulation of the proposed CLSCN are explained as follows:

2.1. Assumptions

The assumptions of the proposed CLSCN are:

- The chain considers multiple types of products;
- The demands are fixed and known;
- The disruptions occur with a known probability and the failure of a DC does not impact the operation of other DCs;
- The DCs charge the customer for repairing a product without a warranty;
- A collecting fee is inflicted on the manufacturer, payable to the DCs, for every returned product covered by a warranty;
- The profit gained by the customer from reworking the product himself or through routine maintenance (instead of returning it to the chain) is calculated by the difference between the final value of the reworked item and the cost of reworking it;
- A fixed price is imposed on the chain for opening a manufacturing or distribution facility;
- The cost of remanufacturing an item is considered lower than the manufacturing cost and the sale price to the DCs (i.e., $ps_{pa} \leq C_{pa} \leq pf_{pa}; \forall p \in P, a \in A$);
- For simplicity, the warranty validation is embedded in the model as a stage of quality check. In other words, if the damage to the product is covered by the warranty, the quality of the returned product is higher than the minimum quality required for remanufacturing (i.e., $q_{ja} \geq qrem_a; \forall j \in J, a \in A$);
- The items returned to the DCs undergo a primary quality check and are sorted based on a predefined

segmentation policy into three categories of remanufacturing, repairing, or recycling;

- The repair price of the products for the customers is assumed higher than the repair cost inflicted on the DCs (i.e., $ga_{ia} \geq prep_{ia}; \forall i \in I, a \in A$);
- A fixed cost is inflicted on the DCs for shipping the recyclable products to a secondary chain. To ensure profit, the cost is assumed lower than the sale price of such items to the secondary market (i.e., $gc_{ia} \geq pns_{cia}; \forall i \in I, a \in A$);
- If an item is categorized as recyclable after the quality inspection, the DCs buy back the item from the customer for half of its original price;
- Transportation costs are considered for shipping the cargos from the manufacturers to DCs and from the DCs to the customers in the forward flow, as well as transferring from the customers back to the DCs in the reverse flow.

2.2. Notation

Sets and parameters

$P; (p \in P)$	Set of candidate locations for opening a manufacturing facility
$I; (i \in I)$	Set of candidate locations for opening a DC
$J; (j \in J)$	Set of fixed locations for the customer markets
$A; (a \in A)$	Set of different types of products
Co_p	Fixed cost of establishing the p th manufacturing facility
f_i^U	Fixed cost of establishing the i th DC with disruption
f_i^R	Fixed cost of establishing the i th DC without disruption
C_{pa}	The cost of producing the a th product by the p th manufacturer
pf_{pa}	The sales price of the a th product by the p th manufacturer to the DCs
ps_{pa}	The cost of remanufacturing the a th product by the p th manufacturer
pdf_{ja}	The price of the a th original product sold by a DC to the j th customer market
D_{ja}	The demand for the a th product from the j th customer market
α_{ja}	The return rate of the a th product from the j th customer market to the DCs
β_{ja}	The rework rate of the a th product determined by the j th customer
$qrep_a$	The minimum quality required for repairing the a th type of product

$qrem_a$	The minimum quality required for remanufacturing the ath type of product
q_{ja}	The quality of the ath product returned by the j th customer
$prep_{ia}$	The repair cost of the ath product by the i th DC (inflicted on the DC)
pns_{cia}	The cost of sending the ath product through the i th DC to the secondary chain
ga_{ia}	The repair price of the ath product by the i th DC (inflicted on the customer)
gb_{ipa}	The sale price of the ath product sent from the i th DC to the p th manufacturer for remanufacturing
gc_{ia}	The cost of selling the ath product to the secondary chain by the i th DC
tf_{ja}	The value of the ath reworked product by the j th customer
ef_{ja}	The cost of reworking the ath product by the j th customer
h_{pia}	The cost of transporting the ath product from the p th manufacturer to the i th DC
h_{ija}^P	The cost of transporting the ath product from the i th primary DC to the j th customer
h_{ija}^B	The cost of transporting the ath product from the i th supporting DC to the j th customer
he_{jia}^P	The cost of transporting the ath product from the j th customer to the i th primary DC
he_{jia}^B	The cost of transporting the ath product from the j th customer to the i th supporting DC
$1 - po_i$	Probability of disruption in the i th DC
M	A large positive number

2.3. Decision variables

BB_{pa}	The number of the ath products produced by the p th manufacturer and bought by the DC s
B_{pia}	The number of the ath products sent from the p th manufacturer to the i th DC
$pdcsr_{ja}$	The sales price of the ath recyclable product returned by the j th customer to a DC
RA_{jia}	The number of the ath products returned by the j th customer to the i th DC for remanufacturing

RB_{jia}	The number of the ath products returned by the j th customer to the i th DC for repairing
RC_{jia}	The number of the ath products returned by the j th customer to the i th DC for recycling in the secondary chain
QA_{ia}	The total number of the ath products returned to the i th DC for remanufacturing
QB_{ia}	The total number of the ath products returned to the i th DC for repairing
QC_{ia}	The total number of the ath products returned to the i th DC to be recycled in the secondary chain
qA_{ipa}	The number of the ath products shipped from the i th DC to the p th manufacturer for remanufacturing
x_p	Binary variable deciding whether or not to open the p th manufacturing facility
y_i^U	Binary variable deciding whether or not to establish the i th DC with disruption
y_i^R	Binary variable deciding whether or not to establish the i th DC without disruption
T_{ija}^P	1, if the <i>primary</i> allocation to satisfy the demands for the ath product by the j th customer is through the i th DC , and 0 otherwise
T_{ija}^B	1, if the <i>supporting</i> allocation to satisfy the demands for the ath product by the j th customer is through the i th DC , and 0 otherwise
T_{ija}^S	1, if the <i>primary and supporting</i> allocations to satisfy the demands for the ath product by the j th customer is through the i th DC simultaneously, and 0 otherwise
A_{ja}	1, if the ath product returned by the j th customer is remanufactured, and 0 otherwise
B_{ja}	1, if the ath product returned by the j th customer is repaired, and 0 otherwise
C_{ja}	1, if the ath product returned by the j th customer is sent to be recycled in the secondary chain, and 0 otherwise

2.4. Problem formulation

The main objective function in Eq. (1) maximizes the profit of the manufacturers (Z_1), the DC s (Z_2), and

the customers (Z_3), simultaneously. The first objective function (Eq. (2)) is calculated by the difference in the production profit, the cost of remanufacturing, facility establishment, and the cost of transportation from the manufacturer to the DCs. The second objective in Eq. (3) measures the final profit of DCs by calculating thirteen separate statements as follows: the revenue gained by the DCs from selling original products to the customer plus the DCs' profit by selling the returns under warranty to the manufacturer for remanufacturing plus the sale profit of sending the recyclable items to the secondary chain plus the profit from repairing the returned products minus the cost of purchasing the products from the manufacturers minus the cost of buying the recyclable returns from the customer minus the fixed costs of establishing the primary and supporting DCs and transportation costs from the primary and supporting DCs to the customer and vice versa, while extracting the overlap in simultaneous allocations. The third objective in Eq. (4) calculates the customer profit by measuring the sum of the revenues from selling the recyclable products to the DCs plus the profit from reworking the products by the customers minus the cost of purchasing the products from the DCs minus the repair cost of an item, payable to the DCs.

$$y = \max(Z_1, Z_2, Z_3), \quad (1)$$

$$\begin{aligned} Z_1 = & \sum_p \sum_a (pf_{pa} - C_{pa}) BB_{pa} \\ & - \sum_p \sum_a \sum_i ps_{pa} q A_{ipa} - \sum_p x_p C o_p \\ & - \sum_p \sum_i \sum_a h_{pia} B_{pia}, \end{aligned} \quad (2)$$

$$\begin{aligned} Z_2 = & \sum_i \sum_j \sum_a pdf_{ja} D_{ja} (T_{ija}^P + T_{ija}^B - T_{ija}^S) \\ & + \sum_i \sum_p \sum_a gb_{ipa} \times q A_{ipa} \\ & + \sum_i \sum_a (gc_{ia} - pns_{cia}) Q C_{ia} \\ & + \sum_i \sum_a (ga_{ia} - prep_{ia}) Q B_{ia} - \sum_p \sum_a BB_{pa} pf_{pa} \\ & - \sum_j \sum_a \sum_i pdcsr_{ja} \alpha_{ja} D_{ja} (T_{ija}^P + T_{ija}^B - T_{ija}^S) \\ & - \left(\sum_i y_i^U f_i^U + \sum_i y_i^R f_i^R \right) \end{aligned}$$

$$\begin{aligned} & - \sum_i \sum_j \sum_a (1 - po_i) D_{ja} h_{ija}^P T_{ija}^P \\ & - \sum_i \sum_j \sum_a po_i D_{ja} h_{ija}^B T_{ija}^B \\ & - \sum_i \sum_j \sum_a (1 - po_i) \alpha_{ja} D_{ja} h_{ija}^P T_{ija}^P \\ & - \sum_i \sum_j \sum_a po_i \alpha_{ja} D_{ja} h_{ija}^B T_{ija}^B, \\ & + \sum_i \sum_j \sum_a po_i D_{ja} (h_{ija}^B - h_{ija}^P) T_{ija}^S \\ & + \sum_i \sum_j \sum_a po_i \alpha_{ja} D_{ja} (h_{ija}^B - h_{ija}^P) T_{ija}^S, \end{aligned} \quad (3)$$

$$\begin{aligned} Z_3 = & \sum_i \sum_j \sum_a pdcsr_{ja} \alpha_{ja} D_{ja} (T_{ija}^P + T_{ija}^B - T_{ija}^S) \\ & + \sum_i \sum_j \sum_a (tf_{ja} - ef_{ja}) \times \beta_{ja} D_{ja}, \\ & \times (T_{ija}^P + T_{ija}^B - T_{ija}^S) - \sum_i \sum_j \sum_a pdf_{ja} D_{ja} \\ & \times (T_{ija}^P + T_{ija}^B - T_{ija}^S) - \sum_i \sum_a ga_{ia} Q B_{ia}, \end{aligned} \quad (4)$$

$$BB_{pa} = \sum_i B_{pia} \quad \forall p \in P, a \in A, \quad (5)$$

$$\begin{aligned} & \sum_p \sum_i B_{pia} + \sum_i (Q B_{ia} + Q A_{ia}) = \\ & \sum_j \sum_i D_{ja} * (T_{ija}^P + T_{ija}^B - T_{ija}^S) \quad \forall a \in A, \end{aligned} \quad (6)$$

$$\begin{aligned} & \sum_i \alpha_{ja} D_{ja} (T_{ija}^P + T_{ija}^B - T_{ija}^S) = \\ & \sum_i (RA_{jia} + RB_{jia} + RC_{jia}) \quad \forall j \in J, a \in A, \end{aligned} \quad (7)$$

$$\sum_i T_{ija}^P = 1, \sum_i T_{ija}^B = 1 \quad \forall j \in J, a \in A, \quad (8)$$

$$T_{ija}^S \leq T_{ija}^P, T_{ija}^S \leq T_{ija}^B \quad \forall i \in I, j \in J, a \in A, \quad (9)$$

$$T_{ija}^P \leq (y_i^U + y_i^R), T_{ija}^B \leq y_i^R \quad \forall i \in I, j \in J, a \in A, \quad (10)$$

$$(y_i^U + y_i^R) \leq 1 \quad \forall i \in I, \quad (11)$$

$$\sum_i y_i^R \geq 1, \quad (12)$$

$$\begin{cases} \text{if } (q_{ja} \geq qrem_a) \rightarrow (A_{ja} = 1, pdcsr_{ja} = 0) \\ \text{if } (qrem_a \geq q_{ja} \geq qrep_a) \rightarrow (B_{ja} = 1, pdcsr_{ja} = 0) \\ \text{if } (q_{ja} \leq qrep_a) \rightarrow (C_{ja} = 1, \\ pdcsr_{ja} = 0.5 \times pdf_{ja}) \end{cases}$$

$$\forall j \in J, a \in A, \quad (13)$$

$$QA_{ia} = \sum_j RA_{jia} \quad \forall i \in I, a \in A, \quad (14)$$

$$QB_{ia} = \sum_j RB_{jia} \quad \forall i \in I, a \in A, \quad (15)$$

$$QC_{ia} = \sum_j RC_{jia} \quad \forall i \in I, a \in A, \quad (16)$$

$$\sum_j RA_{jia} = \sum_p qA_{ipa} \quad \forall i \in I, a \in A, \quad (17)$$

$$\sum_j D_{ja} * \alpha_{ja} * A_{ja} * (T_{ija}^P + T_{ija}^B - T_{ija}^S) = QA_{ia}$$

$$\forall i \in I, a \in A, \quad (18)$$

$$\sum_j D_{ja} * \alpha_{ja} * B_{ja} * (T_{ija}^P + T_{ija}^B - T_{ija}^S) = QB_{ia}$$

$$\forall i \in I, a \in A, \quad (19)$$

$$\sum_j D_{ja} * \alpha_{ja} * C_{ja} * (T_{ija}^P + T_{ija}^B - T_{ija}^S) = QC_{ia}$$

$$\forall i \in I, a \in A, \quad (20)$$

$$y_i^U \leq \sum_p \sum_a B_{pia}, y_i^R \leq \sum_p \sum_a B_{pia} \quad \forall i \in I, \quad (21)$$

$$\sum_i \sum_a B_{pia} \leq M * x_p, \sum_a BB_{pa} \leq M * x_p$$

$$\forall p \in P, \quad (22)$$

$$\begin{cases} y_i^U, y_i^R, x_p, C_{ja}, B_{ja}, A_{ja}, T_{ija}^S, T_{ija}^B, T_{ija}^P \in \{0, 1\} \\ qA_{ipa}, QC_{ia}, QB_{ia}, QA_{ia}, RA_{jia}, RB_{jia}, RC_{jia}, \\ B_{pia}, BB_{pa}, M \in \mathbb{Z}^+ \\ pdcsr_{ja} \geq 0 \end{cases} \quad (23)$$

Constraint (5) ensures that all the manufactured products are sent to the DCs. Constraint (6) indicates that the sum of original, repaired, and remanufactured products of a certain type sent to the DCs should be equal to the customers' demand for that type of product. Constraint (7) indicates that the returns sent back to the DCs should be either remanufactured, repaired, or recycled. Constraint (8) ensures that each customer is assigned only to one primary DC

and/or one supporting DC. Constraint (9) considers an overlap when one customer is simultaneously assigned to the same DC in both primary and supporting allocations. Constraint (10) states that in the primary allocation, a customer can be assigned to any DC with(out) disruption, while in the supporting allocation, customers may only be assigned to a DC without disruption. Constraint (11) ensures that only one DC with or without disruption is established in any candidate site. Constraint (12) ensures that at least one DC without disruption is built to handle the supporting allocations.

Constraint (13) sorts the returned items in terms of quality. The first statement ensures that the high-quality returns, covered by the warranty contract, are sent for remanufacturing. The second condition states that if the quality of the returned product is lower than the prerequisite for remanufacturing (i.e., the warranty is void), but higher than the required quality for repairing, then it is sent for repair. Otherwise, if the quality is lower than the requirements for remanufacturing or repairing, it is labelled as recyclable items and shipped to another chain. Moreover, the sale price of recyclable items is set to half the price of the original products. For simplicity, this nonlinear equation can be linearized via the well-known *if-then* conversion method [23].

Constraints (14) to (16) calculate the total number of products sent to the DCs for remanufacturing, repairing, and recycling, respectively. Constraints (17) ensures that all the products with valid warranty returned by the customer are sent to the manufacturer via the DCs. In the backward chain, Constraints (18) to (20) ensure that the collected items for remanufacturing, repairing, and recycling, respectively, are sent to their corresponding centers/chain. Constraint (21) ensures that a DC with/out disruption is opened to receive the products from the manufacturers. Constraint (22) sets a maximum capacity for the manufacturers' production and the number of cargos shipped to the DCs. Constraint (23) shows the range of the decision variables.

3. Solution approach

The RLTP method covers all types of multiple objective problems and is often used to tackle mixed-integer and nonlinear models or bounded, nonconvex decision space. This approach is a weighting vector space reduction approach based on the rationale that by sampling a weighted sequence of progressively smaller numbers of nondominated solutions at each iteration, a final solution (or a near-optimal solution) will be found to satisfy the decision-maker [24]. Due to the repeated sampling process, the algorithm is proved to have a *multiple starting point* property, which prevents it from getting trapped in local optima [25]. For a

typical multi-objective maximization problem with F objectives, i.e., $\max\{f_k(x); x \in X\}; \forall k = 1, \dots, F$, this method can be explained as follows:

Step 1- Parameters setting and reference vectors

1. Determine the number of non-dominated solutions (N) to be presented to the decision-maker per stage ($N \geq F$).
2. Calculate the reference objective vector (y^{**}) as follows:

$$y^{**} = (y_1^{**}, y_2^{**}, \dots, y_F^{**}),$$

$$y_k^{**} = \max\{f_k(x); x \in X\} + \varepsilon_k; \quad \forall k = 1 : F, \quad (24)$$

where $\varepsilon_k; \forall k = 1 : F$ are moderately small, computationally significant, positive values [25].

3. Set the initial value for the Reservation Level of the k th objective ($RL_k = -\infty; \forall k = 1:F$).
4. Set the value for the reduction factor $r \in (0, 1)$, where the smaller values shrink the objective region more rapidly.
5. Specify the number of required iterations.

Step 2- Weight generation

Generate at least $2N$ randomly generated and widely dispersed λ - vectors via Eq. (25):

$$\Lambda = \left\{ \lambda \in R^F \mid \lambda_k \in (0, 1), \sum_{k=1}^F \lambda_k = 1 \right\}. \quad (25)$$

Step 3- Optimization

The problem in Eqs. (26)–(29) for each λ - vector calculated in Step 2 is solved where ρ is a sufficiently small, numerically significant, positive scalar in the recommended range of $\rho \in (0.0001 - 0.01)$.

$$\min \left\{ \alpha - \rho \sum_{k=1}^F f_k(x) \right\} \quad (26)$$

s.t.:

$$x \in X, \quad (27)$$

$$\alpha \geq \lambda_k (y_k^{**} - f_k(x)) \geq 0 \quad \forall k = 1, \dots, F, \quad (28)$$

$$f_k(x) \geq RL_k \quad \forall k = 1, \dots, F. \quad (29)$$

Next, from the resultant solution set, the N number of most diverse solutions is selected and presented to the decision-maker. If the decision-maker is satisfied with the results, the procedure stops; otherwise, the algorithm proceeds to the next stage.

Step 4- Adjustment

This step is a more interactive stage, where the decision-maker is asked to divide the solutions into two categories: “most preferred” and “least preferred”.

Values for $RL_k; \forall k = 1, \dots, F$ are adjusted according to the decision-maker’s opinion, or based on Eq. (30) proposed by Reeves and Macleod [26], where $CSWV_K$ is the worst value in the set of all the current solutions and $MPWV_K$ is the worst value in the most preferred subset of solutions.

$$RL_k = MPWV_k + r(MPWV_k - CSWV_k). \quad (30)$$

After adjusting the RL_k , the algorithm returns to Step 2.

4. Model validation

In this section, the RLTP method is applied to the proposed model in Section 2 via a numerical example. In this case, two manufacturers (i.e., $P = 2$) ship the products to two DCs (i.e., $I = 2$), where the demands from two types of products (i.e., $A = 2$) are received from three customer markets (i.e., $J = 3$). Moreover, the disruption probability is randomly drawn from a uniform distribution (0 -1) and is set as $po_1 = 0.6$, $po_2 = 0$, and let $M = 100000000$. Other values for the initial parameters were borrowed from a CLSCN by Masoudipour [8] and summarized in Table 1. For the relation between the parameters and an extensive sensitivity analysis, the interested reader is referred to the aforementioned paper. The experiments in this paper are executed via the IBM CPLEX Studio software on a PC with the following configurations: CPU Core i7, Windows 10, and 8 GB of RAM.

In the first step, for the three objectives of the problem, it is decided to present three solutions to the decision-maker per iteration ($F = N = 3$). The reference objective vectors are calculated and shown in Table 2, where the maximum solution per objective is indicated by bold values. The reduction factor r is set to 0.0001 and let $RL_k = -\infty; \forall k = 1:3$, $\varepsilon_k = 0.0001; \forall k = 1:3$.

In the second step, six distinct weight vectors were randomly generated via Eq. (25) and summarized in the first consecutive rows of Table 3. In the third step, the corresponding RLTP model was solved for the six λ -vectors considering $\rho = 0.0001$ and the objective values per vector are depicted in the third to sixth rows of Table 3. The final row of Table 3 shows the corresponding objective value of Eq. (26) for each vector.

In this instance, the decision-maker is not satisfied with the results and defines the most preferred subset solutions as $\{2,1\}$ and the least preferred subset as $\{3,4,5,6\}$.

Thus, the $RL_k; \forall k = 1, 2, 3$ are adjusted for the next iteration as follows and the algorithm returns to Step 3:

$$\begin{aligned} RL_1 &= 86457 + (0.0001 * (86457 - 56176.99)) \\ &= 86460.03, \end{aligned}$$

Table 1. Parameters of the numerical example.

Parameter	Value	Parameter	Value	Parameter	Value
D_{ja}	$\begin{bmatrix} 200 & 200 \\ 400 & 300 \\ 600 & 400 \end{bmatrix}$	h_{pia}	$\begin{bmatrix} [[3, 3][3, 3]] \\ [[3, 3][3, 3]] \end{bmatrix}$	$qrep_a$	50, 50
α_{ja}	$\begin{bmatrix} 0.2 & 0.2 \\ 0.4 & 0.4 \\ 0.6 & 0.4 \end{bmatrix}$	tf_{ja}	$\begin{bmatrix} 10 & 10 \\ 10 & 10 \\ 10 & 10 \end{bmatrix}$	$qrem_a$	70, 70
$f_i^R = Co_p$	$\begin{bmatrix} 3 & 3 \end{bmatrix}$	ps_{pa}	$\begin{bmatrix} 5 & 5 \\ 5 & 5 \end{bmatrix}$	β_{ja}	$\begin{bmatrix} 0.1 & 0.1 \\ 0.2 & 0.2 \\ 0.3 & 0.2 \end{bmatrix}$
q_{ja}	$\begin{bmatrix} 60 & 40 \\ 40 & 20 \\ 65 & 90 \end{bmatrix}$	C_{pa}	$\begin{bmatrix} 60 & 60 \\ 60 & 60 \end{bmatrix}$	$prep_{ia} = gc_{ia}$	$\begin{bmatrix} 10 & 10 \\ 10 & 10 \end{bmatrix}$
pf_{pa}	$\begin{bmatrix} 100 & 100 \\ 100 & 100 \end{bmatrix}$	ga_{ia}	$\begin{bmatrix} 30 & 30 \\ 30 & 30 \end{bmatrix}$	pns_{ia}	$\begin{bmatrix} 4 & 4 \\ 4 & 4 \end{bmatrix}$
pdf_{ja}	$\begin{bmatrix} 120 & 120 \\ 120 & 120 \\ 120 & 120 \end{bmatrix}$	f_i^U	$\begin{bmatrix} 2 & 2 \end{bmatrix}$	$h_{ija}^P = h_{ija}^B$	$\begin{bmatrix} [[5, 5][5, 5][5, 5]] \\ [[5, 5][5, 5][5, 5]] \end{bmatrix}$
gb_{ipa}	$\begin{bmatrix} [[10, 10][10, 10]] \\ [[10, 10][10, 10]] \end{bmatrix}$	ef_{ja}	$\begin{bmatrix} 4 & 4 \\ 4 & 4 \\ 4 & 4 \end{bmatrix}$	$he_{ija}^P = he_{ija}^B$	$\begin{bmatrix} [[5, 5][5, 5]] \\ [[5, 5][5, 5]] \\ [[5, 5][5, 5]] \end{bmatrix}$

Table 2. The pay-off table of the numerical example.

Objectives	Z_1	Z_2	Z_3
Z_1	112357	112354	56174
Z_1	156795	174675	75417
Z_3	-484320	-484320	-242160

$$RL_2 = 165155 + (0.0001 * (165155 - 75417))$$

$$= 165164,$$

$$RL_3 = -459240 + (0.0001 * (-459240 + 459240))$$

$$= -459240. \quad (31)$$

Table 4 summarizes the results of the second and third iterations. It can be seen that at iteration 2, the objective values for solutions 1, 3, 4, 5, and 6 are similar, while their corresponding RLTP objectives are different. This is due to different α values in Eq. (28) that result from variable λ -vectors. Such results show the efficiency of the RLTP method since the algorithm

is trapped in a local optimum, while a shift in the λ -vectors in solution 2 can move the searching area to other promising regions.

Updating the RL_k ; $\forall k = 1, 2, 3$ for the third iteration with the most preferred subset solutions set as $\{2\}$ and least preferred subset as $\{1, 3, 4, 5, 6\}$ leads to $RL_1 = 101258.11$, $RL_2 = 173895.28$, and $RL_3 = -455883.09$. The model returns the “No solution” warning and the algorithm is terminated, returning solutions 1 and 2 as the two Non-Dominated Solutions (NDS) of the numerical example. This heuristic can be easily applied to problems of larger scale where the opinion of the decision-maker directs the progress of the algorithm and sets its termination point.

Next, for the same numerical example, the performance of RLTP method is tested against the augmented ε -constraint algorithm [27], which has a similar structure in finding the non-dominated values by iteratively restricting the searching area. Three well-known performance metrics are used for comparison [28]: the overall non-dominated vector generation (ONVG), the normalized maximum spread (MS), and the mean ideal

Table 3. RLTP solutions of the numerical example 1 at the first iteration.

Iteration	1	2	3	4	5	6
λ_1	0.03	0.90	0.35	0.05	0.45	0.33
λ_2	0.95	0.07	0.55	0.05	0.10	0.33
λ_3	0.02	0.03	0.10	0.90	0.45	0.34
z_1	86457	106437	73137	56176.99	70977	71657
z_2	172854	165155	160775	75417.00	76455	105255
z_3	-417960	-459240	-371400	-242160	-280080	-311160
RLTP obj	3531.86	6531.16	13740.74	4973.95	18634.26	23473.42

Table 4. RLTP solutions of the numerical example 1 at the second iteration.

Iteration	1	2	3	4	5	6
λ_1	0.025	0.90	0.35	0.03	0.15	0.33
λ_2	0.94	0.04	0.40	0.01	0.40	0.33
λ_3	0.035	0.06	0.25	0.96	0.45	0.34
z_1	90157	101257	90157	90157	90157	90157
z_2	171075	173895	171075	171075	171075	171075
z_3	-424920	-455880	-424920	-424920	-424920	-424920
RLTP Obj	6412.96	12841.27	45706.36	175465.96	82258.36	62154.76

Table 5. Comparison between RLTP and ε -constraint algorithms for the numerical example 1.

Metric	ε -constraint	RLTP
ONVG	18	8
MS	0.5649	0.8374
MID	424913.65	403910.05

distance (MID). The ONVG counts the number of NDS obtained from an algorithm; ergo, higher values of ONVG are desirable. The normalized MS indicates the distance between the NDS in the obtained Pareto front. Thus, values near 1 for MS show a better exploration of an algorithm. The MID metric is an indicator of closeness between the achieved Pareto solutions and the ideal point per objective; hence, lower values of MID are preferable. Table 5 summarizes the comparison results between the two algorithms.

As can be seen in Table 5, the ε -constraint method finds more NDS than RLTP. However, the diversity of the NDS found by RLTP is better, as indicated by the higher value of *MS*. Moreover, the convergence and the quality of the solutions found by RLTP are preferable, as depicted by the lower values of *MID*.

5. Experiments and results

This section investigates the effects of key parameters on the objective values. The first group of parameters points to the segmentation policy for remanufacturing, repairing, and recycling corresponding to the param-

eters $qrem_a$ and $qrep_a$ in the model presented in Section 2. The second parameter is the disruption probability, po_i , which has been tested to analyze its effect on the locations, allocations, and overall profits. The remaining parameters are similar to the first example in Section 4. For simplicity, the λ -vectors in Table 4 are applied to all the instances.

5.1. Testing the quality of the returned products

In the backward flow, the quality of returns is a deciding factor in the segmentation process, which in turn affects the prices/costs and ultimately, the profit of each entity in the chain. For instance, to examine the quality-profit relationship in the model, it is assumed that the quality of each return is lower than 100% and falls in the range of [0,90]. The defined range of quality for remanufacturing, repairing, and recycling is set at [70,90], [50,70), and [0,50), respectively. For instance, a return with 25% of quality in comparison to the original product is shipped to another chain for recycling, an item with 60% of quality is sent for repair, and a product with 85% of quality is covered by the warranty agreement and is fit for remanufacturing. For simplicity, it is assumed that at a specific point in time, the quality of all the returned items is similar. The model is solved for all the three ranges of quality and the nondominated solutions are provided in Table 6, where the quality range [0,50) returns four nondominated solutions, while ranges [50,70) and [70,90] find two solutions per objective. Furthermore, Figure 2

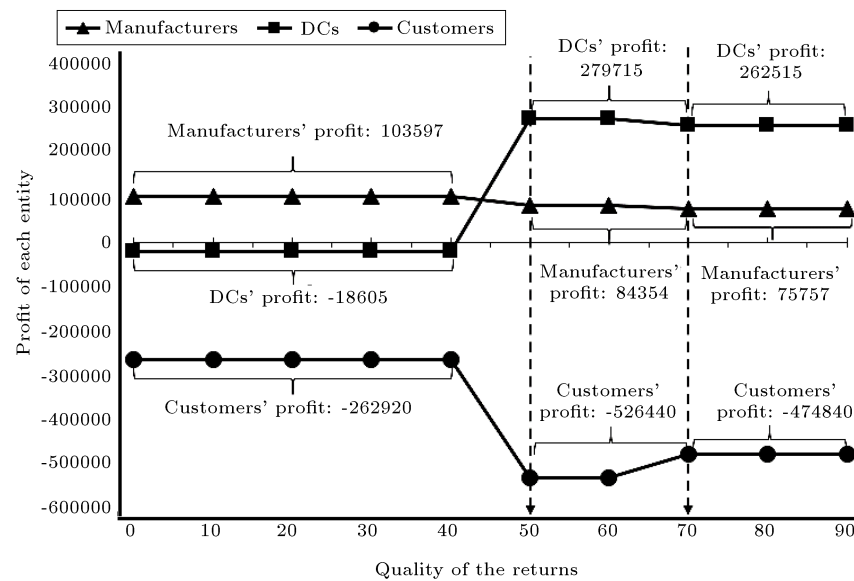


Figure 2. Quality of returns versus the resultant profits.

Table 6. Non-dominated solutions of different qualities.

Quality ranges	[0 – 50)	[50 – 70)	[70 – 90]
Z_1	103597	84354	75757
Z_2	-18605	279715	262515
Z_3	-262920	-526440	-474840
Non-dominated solutions	Z_1	92497	83617
	Z_2	-15305	267575
	Z_3	-239520	-512280
	Z_1	85097	-
	Z_2	-17865	-
	Z_3	-218040	-
	Z_1	96197	-
	Z_2	-17085	-
	Z_3	-246480	-

depicts the return quality versus the gained profit for each entity of the CLSCN. According to Figure 2 and Table 6, the DCs profit the most in the quality range [50,70) when they can increase their income by selling the repaired items to the customers for higher prices than the repairing costs. Another source of profit is available to the DCs in the range [70,90] when the DCs collect the high-quality products covered by the warranty and sell them to the manufacturers. However, once the quality is reduced to the range [0,50), the DCs receive lower profit since the recyclable items are sold to the secondary chain for half their actual prices.

The main revenue for the manufacturer is by selling the original products to the DCs in the forward flow; thus, its profit is almost constant except for the price paid to the DCs for collecting the products covered by the warranty agreement in the range [70,90].

The only revenue for the customer is through selling the low-quality items in the range [0,50) to the secondary chains via the DCs; thus, the customer profits the most by simply returning the end-of-life products. The lowest profit for this group is in the range [50,70) when the customer compensates the DCs for repairing the item. The warranty coverage in the range [70,90] reduces the costs inflicted on the customers and increases their profits.

Overall, it can be deduced that in such a CLSCN, returns with medium-range quality [50,70) are preferred by the DCs and the manufacturers, while due to the incentives offered by the DCs for recyclable items, the customer prefers low-quality returns. The highest average profit of the entire chain (equal to 305722.67) is achieved in the range [50,70) for objective values $z_1 = 83617$, $z_2 = 267575$, and $z_3 = -512280$ depicted in Table 6.

5.2. Testing on the probability of disruption

In the forward flow, candidate sites are dedicated to open primary and/or supporting DCs considering the probability of disruption (i.e., $po_i; \forall i \in I$). By default, opening a primary DC is less expensive and more cost-effective (i.e., $f_i^R > f_i^U$), while establishing at least one supporting DC without the possibility of disruption is essential to ensure an uninterrupted flow of service and the availability of a DC at all times. The two DCs are considered similar in all aspects (except for the probability of disruptions) and thus,

Table 7. Solutions for different probability of disruption.

Row	$[p_{o1}, p_{o2}]$	$[0.2, 0]$	$[0.4, 0]$	$[0.6, 0]$	$[0.8, 0]$	$[1, 0]$
1	# of NDS	19	19	21	21	21
2	z_1	88621.21	89906.47	89683.67	89683.67	89683.67
3	z_2	137315.89	136056.95	138186.24	140001.57	141816.90
4	z_3	-390423.16	-390480.00	-390200.00	-390200.00	-390200.00
5	Mean	-54828.68	-54838.85	-54110.03	-53504.92	-52899.80
6	y_1^U	0.84	0.84	0.81	0.90	1.00
7	y_2^U	0.00	0.00	0.00	0.00	0.00
8	y_1^R	0.16	0.16	0.19	0.10	0.00
9	y_2^R	1.00	1.00	1.00	1.00	1.00
10	x_1	0.11	0.37	0.29	0.43	0.48
11	x_2	0.89	0.63	0.71	0.57	0.52

Table 8. Decisions on facility establishment for disruption probability (0.6 – 0).

Objectives trade-offs		Manufacturer		Open DC with disruption		Open DC without disruption		Non-dominated solutions		
		x_1	x_2	y_1^U	y_2^U	y_1^R	y_2^R	z_1	z_2	z_3
z_1	Max	0	1	1	0	0	1	112357	174675	-484320
	Min	1	1	0	0	1	1	56174	75414	-242160
z_2	Max	1	1	1	0	0	1	112354	174675	-484320
	Min	1	1	0	0	1	1	82074	71354	-308520
z_3	Max	1	1	0	0	0	1	56174	75417	-242160
	Min	1	1	1	0	0	1	112354	174675	-484320

the analysis of an instance with $p_{o1} = 0$, $p_{o2} = 1$ can be interchangeably extended to the probabilities of $p_{o1} = 1$, $p_{o2} = 0$. In the following experiments, the values for p_{o1} are progressively increased from 0 to 1 (with the steps of 0.2), while the second DC is considered unavailable at all times (i.e., $p_{o2} = 0$). Table 7 summarizes the average values of all the NDS found for different sets of disruptions. It should be noted that to ensure valid results from Eq. (3), at least one of the DCs should face disruption ($p_{o1} > 0$). The first row in Table 7 indicates the number of NDS found per test for a specific set of probability disruptions. The average values per objective for the achieved solutions are depicted in rows 2 to 4. The mean value for each test in row 5 combines the three objectives with a similar weight (i.e., 1/3) and is used to showcase a trend in the data. This variable indicates that increasing the value of p_{o1} (i.e., decreasing the probability of disruption $1 - p_{o1}$) improves the overall performance of the chain (highlighted by bold values in row 5). The decisions related to opening a DC with/out the risk of disruption (primary or supporting DC) are summarized in rows 6 to 9. As can be seen in rows 6 and

8, following the reduction of disruption probability for the first DC (increase in the value of p_{o1}), the model prefers to construct a primary DC (on average, 84% to 100% of the times) rather than a supporting DC (on average 0% to 0.16% of the times) so as to minimize the facility establishment costs and improve the DCs' profit. Similarly, in rows 7 and 9, the second DC may be disrupted with the probability of 1; thus, this facility is always established as a supporting DC as depicted by the values of $y_2^R = 1$ for all the instances.

Rows 10 and 11 indicate the decisions on the opening of manufacturing facilities. Since the two manufacturers are considered similar, the model balances the workload between them based on the probability of disruption and ensures that at least one manufacturing site is always opened. Thus, the cumulative values of x_1 and x_2 for all the instances are equal to 1 ($x_1 + x_2 = 1$).

For further analysis, for a mid-range set of disruption probabilities $p_{o1} = 0.6$, $p_{o2} = 0$, the optimal limits for a single objective (maximum and minimum values) are found in Table 8. The first two rows in Table 8 show that if only the profit of the manufacturer is to be considered, the manufacturers

gain the most by opening *one* manufacturing site, one primary *DC*, and a supporting *DC*. However, once a second manufacturing facility is added and both *DCs* are built as supporting *DCs*, the manufacturers' profit is reduced to its lowest. This can be explained based on the additional cost of establishing a manufacturing facility and the fact that the manufacturer has to cover more remanufacturing demands by the establishment of two supporting *DCs* (rather than one primary and one supporting *DCs*). The *DCs* profit the most once both manufacturers are operating as the *DCs* can increase their gain by selling more original products. Moreover, the profit of the *DCs* is reduced as more supporting *DCs* are constructed since they cost higher than their primary counterparts.

The customers prefer a smaller number of established *DCs* to minimize the transportation costs, while they remain indifferent to the opening of either manufacturing sites as long as at least one (or both) facility covers the remanufacturing processes.

6. Managerial insights

This section provides some insights into the way decisions are made regarding the mathematical model has been provided in this paper:

- A closed-loop supply chain leads to the collection and re-usage of the residual value of returned products and depending on the recovery options, a zero-waste chain may be created;
- In the forward and backward flows, the appropriate location of facilities and allocation of customers result in higher profit, better responsiveness, and overall customer satisfaction;
- The policies regarding the segmentation of returned products should be defined based on their quality. Thus, the recovery route with the least cost and highest profit can be easily distinguished considering the quality of the returns;
- Once the returned items of the present chain are of so low a quality that cannot be used in any form, instead of regarding them as waste, they can be sold to the supply chain of another industry;
- Due to the weather conditions, floods, earthquakes, wars, staff strikes, changes in management hierarchy, legislation and government policies, machine breakdown, or human error, any facility in a chain may be unavailable at one time. Thus, the possibility of disruption is a crucial factor to be considered in mathematical models;
- Considering the supporting *DCs* along with the primary ones ensures the constant availability of service even upon the occurrence of disruptions;
- While satisfactory to the customer, a warranty period ought to be designed in a way that it leads to the least cost for the manufacturer. In other words, the warranty period should be related to the quality reduction rate of a product.

7. Conclusion

The proposed tri-echelon Closed-Loop Supply Chain Network (CLSCN) in this paper incorporated the manufacturers, distribution centers, and the customers and considered four policies to handle the returned items remanufacturing by the manufacturer according to the warranty contract, reworking by the choice of the customer, repairing by the Distribution Centers (*DC*), or recycling by selling the items to a secondary chain. The model was solved with Reservation Level-driven Tchebycheff Procedure (RLTP) method, and the tests on the quality segmentation revealed that the manufacturer gained the most profit by increasing the sales of original products in the forward flow. The *DCs* profited the most in the medium-range quality by increasing their income via the sale of repaired items. In addition, customers can maximize their profit by selling the end-of-life products to the *DCs* in the backward chain and benefitting from the cost-reduction options of reworking and warranty agreements. The highest average profit of the entire chain was achieved in the medium-range quality, which could guide the managerial strategies on pricing decisions of the backward chain. The investigation of the probability of disruption depicted that with the reduction of the probability of disruption, the model preferred to open a primary *DC* rather than a secondary *DC*, opened a minimum number of manufacturing and distributing sites to lower the cumulative costs, and improved the overall performance. Future studies on the subject can cover the addition of inventory decisions and demand uncertainty to the model and consider the disruption parameters as fuzzy or grey numbers. Finally, developing other heuristics based on stochastic programming or robust optimization to handle the disruptions can be a suitable avenue for more complex problems.

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