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A sustainable closed-loop location-routing-inventory problem for perishable products

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Abstract. Perishable products may expire if their holding time exceeds their shelf-life. In this study, along with designing a forward flow to distribute perishable products, the remaining perished products at retailers can be gathered for recycling during fresh product distribution. To mitigate waste, recycled products are offered to a secondary market. A mathematical model for this Closed-Loop Location-Routing-Inventory Problem (CL-LRIP) is developed by considering multi-compartment trucks, simultaneous pickup and delivery, technology selection, and the risk of urban traffic. Based on three sustainability pillars, three objective functions are considered. This way, the interests of the network's three main stakeholders are embedded. The proposed model is solved by the Torabi-Hassini method. Two evolutionary algorithms, including Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) and a new hybrid one, are also developed to solve large-sized cases of the NP-complete problem. Statistical tests show the superiority of the hybrid algorithm in the Computational Time (CT) metric, which is about 0.4 NSGA-II's CT. The results indicate the importance of closing the network loop for perishable products. Finally, the sensitivity analysis determined that 83.33% decrease in recycled product's sale price caused 9.08% increase in costs, 2.77% decrease in environmental side-effects, and 5.16% decrease in social objectives, which are significant.

1. Introduction

The distribution type of product wastage involves a remarkable part of losses, especially for perishable products such as food and vegetables [1]. Meanwhile, in some societies, children suffer from malnutrition [2]. Even in some populated developing or developed countries, adults suffer from food poverty [3]. According to Parfitt et al. [3], in 2050, nine billion people are going to be fed by the same earth resources that exist now. Meanwhile, the agriculture fields lose their fertility for agro-food products after several harvests [4]. Perishable products begin to deteriorate when their shelf-life expires. Therefore, some parts of a retailer's perishable inventories can perish in each period because of quality loss, outdatedness, etc. [5].

Sustainable Supply Chain Management (SSCM) refers to designing products and distribution networks, causing no harm to recent or future generations considering the economic, environmental, and social consequences [6]. Thus, satisfaction of all stakeholders in the

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supply chain should be taken into account. According to Eskandarpour et al. [7], there are three main stakeholders in a supply chain, including customers, personnel who are working in the supply chain, and the local community affected by the supply chain activities.

A product can complete its life cycle by integrating forward and reverse logistics in the Closed-Loop Supply Chains (CLSCs). In addition to the forward flow of materials from suppliers to customers, the collection and management of perished products through reusing, recycling, etc. are addressed in CLSCs [8].

To reduce urban wastes, perishable products that have not perished yet but lost their quality can be offered to a secondary market after reprocessing [5]. Govindan et al. [2] stated that low-quality products could be sold at a secondary market at a lower price, especially in societies in which people in various areas have different Maximum Willingness to Pay (MWP). Thus, a CLSC can help reduce resource consumption and waste generation to achieve global sustainability [9].

This paper is among the first studies that deals with a Closed-Loop Location-Routing-Inventory Problem (CL-LRIP) considering (a) simultaneous pickup and delivery for perishable products, (b) the possibility of selling recycled products to a secondary market, (c) the possibility of applying different technologies, each one with specified economic, social, and environmental specifications at DCs and RCs, and (d) applying multi-compartment trucks in a Vehicle Routing Problem (VRP) with simultaneous pickup and delivery to reduce transport costs besides energy and fuel consumption of the trucks. By this contribution, there is no need to use two different fleets for delivering fresh products and picking up the remaining products (visiting each retailer twice). Utilizing multi-compartment vehicles are inspired by Moon et al. [10] who utilized a multi-compartment fleet for different types of products.

This problem is inspired by real-world observations. For instance, some of the applications of the proposed model are in fruit/vegetable distribution networks in which DCs dispatch products to retailers, but the remaining unsold products can be sold at a lower price to workshops, which produce dried fruits/vegetables to supply part of their demand. In the industrial bread case, one of the resources used to supply bread demands (versus bakeries), people usually avoid buying low-quality or stale bread, which can be collected and turned into toasted flour for humans or animals and poultry feed. There are similar examples in dairy industry, fashion industry, and cut flower supply chains, which unsoldflowers can be carried to some workshops to produce dry decorative flowers, scent, etc.

A mathematical model is developed to formulate the CL-LRIP of a network including a supplier, Distribution Centers (DCs), retailers/customers, Recycling Centers (RCs), and a Central Disposal Center (CDC). The proposed model aims to make decision about: the location of active DCs in the CL-LRIP, the product distribution routes from DCs to retailers, the optimal and eco-friendly inventory policy of retailers, the location of the RCs for collecting/recycling perished low-quality products to turn them into the second product. Also, it identifies the impacts of the leading stockholder's utility functions on optimal location, routing, and inventory decisions, the impacts of multi-compartment trucks on CL-LRIP, and the impacts of recycled product sale on sustainability pillars.

In this paper, three objective functions are considered. The first objective function attempts to minimize costs. The second one concentrates on environmental side effects by proposing a new model to calculate them based on the weight of fresh and expired products carried simultaneously by multi-compartment trucks and the distance between nodes. In the third objective function, the impacts of opening DCs/RCs on increasing job opportunities and balanced economic development for local communities, which are two main aspects of Social Responsibility (SR) [11], are considered. The interests of two other groups of stakeholders, including customers and personnel, are maintained by their utility functions.

The remainder of the paper is organized as follows: Section 2 involves a review of related literature. Section 3 presents the mathematical formulation of the problem. Section 4 provides a real-case study, which is solved by an exact method, and two developed multi-objective meta-heuristic algorithms. Section 5 reports numerical results and sensitivity analysis in detail. The final section discusses conclusions and some future directions.

2. Literature review

Following a review of related studies, we found that SSCM was first defined by Seuring and Müller [6] as a balance among economic, environmental, and social aspects. Numerous studies on SSCM have merely focused on economic and environmental issues, perhaps due to international goals set by the European Commission, e.g., reduction of 500 million tons of GHG emissions from the year 2015 to 2035 [12]. However, social aspects of sustainability are a matter of great concern, especially in labor-intensive industries. In Table 1, some social criteria studied in quantitative models are summarized.

Integration of forward and reverse logistics that causes the formation of a CLSC [13] strongly influences three pillars of sustainability. For instance, by using the same facilities/resource/workforce for the distribution and collection and the same fleet for the line-haul and

Table 1. Social criteria considered in some recent SSCM studies.

Article	Problem type	Economic	Environmental	Social
Devika et al. [5]	CLSC network design	Total cost	Environmental impact	Fixed & variable job creation Personnel damage at the time of facility establishment
Rahimi et al. [16]	IRP	Total profit	Noise Emission	Vehicle accidents Number of expired products
Khalili-Damghani et al. [17]	LRP	Total cost	–	Balance of workload of DCs personnel
Zhalechian et al. [11]	LRIP in CLSC	Total cost	Energy consumption CO_2 emission	Job creation Economic development
Rabbani et al. [18]	Transportation LRP	Total cost	Fuel consumption CO_2 emission	Personnel interests (balancing drivers route length) Customers satisfaction (soft time windows)
Sazvar et al. [19]	Transportation Inventory	Total cost	CO_2 emission	Public health
Sazvar and Sepehri [20]	Inventory	Total profit	GHG emission	Job creation for native labor instead of unemployed immigrant labor

back-haul, the amounts of wastes/environmental side-effects as well as costs are reduced [14]. In designing forward and reverse logistics, only strategic decision levels (e.g., Facility Location Problem (FLP)) are taking into account (i.e., facilities are connected only by the flow balancing equations, which are an elementary type of connection) [15]. However, these connections play an important role in energy consumption rates and operational network costs. Therefore, in this study, VRP decisions are integrated. A comprehensive literature review of CLSC was presented by Govindan et al. [8].

Based on sustainable development pillars, since the inventory management of the deteriorating products, divided into perishable and decaying products by Bakker et al. [21], can give rise to environmental protection, job creation, and financial benefits [22], this study focuses on perishable products. Challenges intensify in the case of managing the transportation and vehicle routing of perishable products, given their impact on the environment [23]. A systematic review was conducted on inventory models of perishable products by Chaudhary et al. [24]. Different approaches to modeling perishability of products were found: expiration after passing product shelf life [25,26], expiration of a specific percentage of inventory per period [27,20], a nonlinear holding cost function depending on the product life cycle/amount of remaining inventories [28,29], and combination of the three previously mentioned techniques [30].

Recently, the concept of sustainability is raised in the IRP. Rahimi et al. [16] considered lower selling price for products with a longer age and found that exceeding the shelf life of a product would lead to spoilage. They added the concept of reverse logistics to the IRP to increase the distribution network sustainability for perishable products. Moreover, Rahimi et al. [31] formulated a fuzzy multi-objective IRP model that considers maximizing profit, maximizing service level, and minimizing the GHG emissions of network activities

In this paper, the Location-Routing-Inventory Problem (LRIP) that was introduced by Ahmadi Javid and Azad [32] by integrating the LRP, which is reviewed by Prodhon and Prins [33] with IRP is included in a CLSC. In the LRIP, different decision-making levels including strategic (i.e., location), tactical (i.e., routing), and operational (i.e., inventory) ones are integrated.

A two-stage multi-product LRIP with stochastic demand and travel time was studied by Nekooghadirli et al. [34]. In their two-objective problem, which minimizes the total cost and maximum meantime of delivering commodities to customers, (R, Q) ordering policy with a Safety Stock (SS) is used. A multi-product LRIP with the back-ordered demand and split-sourcing was solved by Ghorbani and Akbari Jokar [35] with the application of the automobile industry. The order and shortage amount and inventory level at the end of the period were added as decision variables. They developed an efficient hybrid imperialist competitive-simulated annealing algorithm to find near-optimal solutions. Tavakkoli-Moghaddam and Raziei [36] considered a bi-objective multi-product LRIP with a heterogeneous fleet and a fuzzy demand, which minimized the cost of the two-echelon network and the total lost sales. They used the Torabi-Hassini's (TH) method to solve the problem by GAMS software. A generalized Benders decomposition method was developed by Zheng et al. to solve an integrated location-inventory-routing problem for the supply chain design [37]. Because of the LRIP complexity, Karakostas et al. [38] solved an LRIP with distribution outsourcing via a variable neighborhood search-based meta-heuristic algorithm.

With the advent of the SSCM, sustainable LRIP has also received the attention of some researchers. Zhalechian et al. [11] formulated the LRIP in a CLSC for the automobile industry by considering three pillars of sustainability (i.e., the economic, environmental, and social impacts). They integrated reverse and forward logistics by using common facilities for collecting and distributing. However, in the current study, the same fleet for forward and backward flows is utilized. In Table 2, a summary of the existing articles that address sustainability along with location, routing, and inventory problems is given.

According to Table 2, a limited number of re-

Table 2. Significant features of the current study versus other related articles.

					Shape of network						Sustainability										
	Sub-problems				One/multi-source		Closed-loop				Main Assumptions						Social objective	Uncertainty		Solution method	
Articles	Location	Routing	Inventory	Simultaneous pickup & delivery	One source	Multi-source	Just forward/reverse flow	Remanufacturing center	Recycling center	Disposal center	Multi-stage	Multi-product	perishability	City legislations	Time windows	Green objectives	1) community, 2) personnel, 3) customer	Stochastic	fuzzy	Exact	Heuristic/meta-heuristic
Ahmadi Javid and Azad [32]	✓	✓	✓			✓	✓											✓		✓	✓
Ramezani et al. [13]	✓				✓			✓		✓	✓	✓					3✓	✓		✓	
Kim et al. [9]			✓	✓	✓			✓					✓					✓		✓	
Devika et al. [5]					✓			✓	✓	✓	✓					✓	1,2✓				✓
Rahimi et al. [16]		✓	✓		✓					✓		✓	✓		✓	✓	2✓			✓	
Zhalechian et al. [11]	✓	✓	✓			✓			✓		✓	✓				✓	1✓	✓	✓		✓
Tavakkoli-Moghaddam & Raziei [36]	✓	✓	✓			✓	✓				✓	✓							✓	✓	
Hiassat et al. [39]	✓	✓	✓			✓	✓					✓	✓								✓
Rahimi et al.[31]		✓	✓		✓		✓					✓	✓			✓	3✓			✓	
Rabbani, et al. [18]	✓	✓				✓	✓				✓	✓		✓	✓	✓	1,3✓				✓
Rafie-Majd et al. [40]	✓	✓	✓		✓		✓				✓	✓	✓					✓		✓	✓
Sazvar, et al. [19]			✓		✓		✓						✓			✓	3✓			✓	
Navazi et al. [41]	✓	✓			✓		✓				✓		✓	✓		✓	1,2✓			✓	
Zheng et al. [37]	✓	✓	✓			✓	✓											✓		✓	
This study	✓	✓	✓	✓	✓				✓	✓	✓		✓	✓	✓	✓	1,2,3✓		✓	✓	✓

searches on the LRIP concentrate on perishable products. For instance, by considering a limited deterministic shelf life for products, Hiassat et al. [39] developed a Mixed-Integer Linear Programming (MILP) model to solve the LRIP for a perishable product. Their results confirm the benefits of integrating different decision levels. Rafie-Majd et al. [40] developed a Lagrangian relaxation algorithm to solve the LRIP for multi-perishable products that should be delivered in a limited time horizon. However, some real assumptions have not been studied in previous models such as gathering perished products via VRP with simultaneous pickup and delivery; using multi-compartment trucks for forward and backward flows; collecting expired products, turning them into the second-hand product in RCs, and selling them in a secondary market; considering all sustainable development pillars; and preserving the interest of three main supply chain stakeholders.

This paper tries to cover the aforementioned gaps. The main contributions of this study are as follows:

- Considering reverse logistics in a CL-LIRP by locating some RCs and, then, selling their recycled products to a secondary market;
- Concentrating on perishable products, technology selection, GHG emission, and the risk of urban traffic along with sustainability requirements in LRIP;
- Considering multi-compartment trucks for simultaneous pickup and delivery in a CL-LRIP. This way, a new formulation is developed to calculate the Fuel/energy Consumption Rate (FCR) and GHG emission of the multi-compartment trucks and other fleets based on their load weight;
- Focusing on the social satisfaction of the three main stakeholders of the supply chain by developing a new quantitative formulation to calculate satisfaction as the social objective function. However, in most studies, just one group of stakeholders is considered;
- Developing two evolutionary algorithms, including a new hybrid, with a new customized solution representation to solve the developed multi-objective large-sized problems.

3. Problem description and mathematical formulation

This study aims to achieve an efficient plan for a sustainable closed-loop network for perishable products by integrating forward and reverse flows. Three echelons of the forward flow are plant, DCs, and retailers. Traffic restrictions of the populated cities on the entry of lorries prohibit a direct connection between the supplier and retailers and add an echelon between a supplier and retailers. In this one source problem, a supplier (e.g., far distant factory, orchard, garden, far-field, and the like) must supply the uncertain demands of retailers through several DCs. Products should first be received by DCs and then, delivered to retailers. Retailers are prioritized based on their loyalty. The location of active DCs, as intermediate facilities with limited capacities, should be selected from some potential points in the city's outskirts (DCs location decision). In addition, the technology level of active DCs should be specified among solar, gasoline, and oil (DCs technology level decision). The number of lorries should also be determined (forward flow transportation decision).

Product delivery should take place in the soft time windows of the DCs. Otherwise, it would incur a penalty cost. A soft time window is also included for retailers/customers. Unlike DCs, the violation of the retailer's time windows affects the satisfaction level of customers in the social criterion. The time of fast unloading and loading products in DCs is ignorable in comparison to other times of distribution activities. Therefore, DCs do not hold inventories.

DCs should deliver products to retailers by some smaller trucks as soon as possible. Since smaller trucks are multi-compartment, the forward and reverse flows are joined together. We attempted to improve network performance by sharing the transportation fleet in the forward and reverse flows. Each compartment of the truck has a limited capacity. The cold compartment for transporting fresh products consumes energy to provide an appropriate cold temperature. Retailers keep inventory until the next visit (order quantities and inventories decisions). The no freezer compartment of the truck is for picking up the retailer's perished products and handing them over to the RCs. The model should also find an optimal location for operated RCs among some potential points (RCs location decision). After connecting the last retailer of the route to an RC, the mission of the multi-compartment truck finishes (multi-compartment VRP with simultaneous pickup and delivery decisions). The risk of urban traffic is also considered, which influences traveling time and time of delivery. There is no necessity for multi-compartment trucks to come back to their departure DCs in each period. Therefore, open VRP is encountered. Keeping the routes open instead of closing them to departure DCs can help drivers reach their home sooner and increase their work satisfaction.

Usable perished products are reprocessed and turned into new products for the secondary market in operated RCs. Value-added products can be sold to a secondary market with a notable price to compensate for the collecting and recycling expenditures. Sending unusable perished products from RCs to bury in the CDC by homogeneous fleet forms a transportation

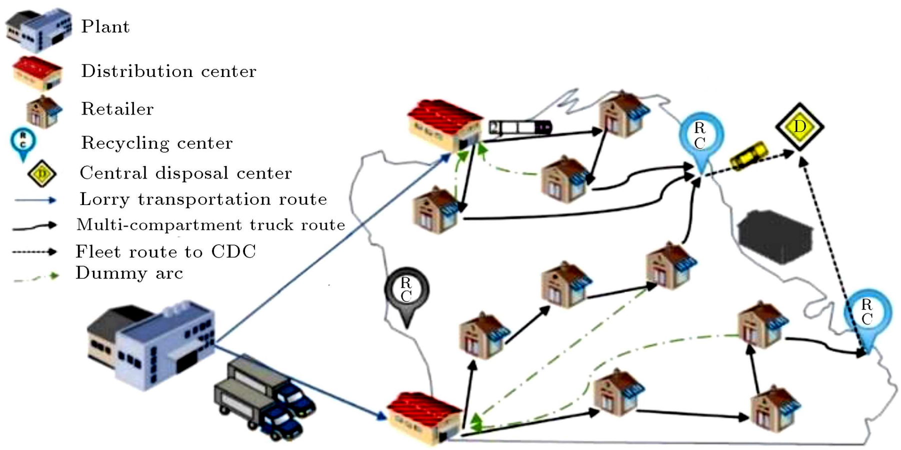

Figure 1. Schematic of the CL-LRIP.

phase at the end (reverse flow transportation decision). A schematic view of the considered CL-LRIP is shown in Figure 1.

The problem has three objective functions according to the three pillars of sustainability. The traditional goal of the problem is to minimize network costs. The second objective function, called the green objective function, tries to minimize energy consumption and destructive environmental effects of activating DCs and operating RCs based on their technology levels; it also minimizes fuel consumption and CO_2 emission of lorries, multi-compartment trucks, and homogeneous fleets based on their traveled distance and the weight of their load. This way, the fuel consumption formulation for classic VRP presented by Soysal [42] is extended to VRP with simultaneous pickup and delivery. The energy consumption of cooling equipment of multi-compartment trucks is calculated by a similar formulation based on a load of fresh products.

The third objective function, called the social objective function, aims to maximize the satisfaction of three main stockholders. This way, the retailers' satisfaction is defined based on a utility function upon considering time windows for retailers. Simultaneously, the DCs' personnel satisfaction is maximized by activating the DCs, which have a reasonable distance from personnel location. For maximizing the local community's satisfaction, improving the economic development of regions besides job creation is considered by allocating the required number of personnel to DCs/RCs.

Assumptions

- The plant has enough capacity to satisfy all retailers' demands;
- The location of the plant, retailers, and CDC is predefined and fixed;
- The plant and DCs do not keep the inventory. The products are fresh while leaving the plant;
- The demands of retailers are uncertain and independent;
- A dummy arc with zero cost and time is considered between the last retailer and the origin DC of a route to model simplicity.

Notations

Indices and sets:

$O \in \{1\}$	Plant
$t \in \{1, 2, ..., T\}$	Time periods
$d \in \{1, 2, ..., D\}$	Potential DCs
$g \in \{1, 2, ..., G\}$	Technology levels of DCs (e.g., gas, solar, and electricity)
$i \in \{1, 2, ..., I\}$	Retailers
$r \in \{1, 2, ..., R\}$	Potential RCs
$s \in \{1, 2, ..., S\}$	Technology levels of RCs
$cdc \in \{1\}$	Central disposal center
$l \in \{1, 2, ..., L\}$	Network personnel location
$m \in \{1, 2, ..., D + I\}$	Potential DCs and retailers nodes
$m' \in \{1, 2, ..., D+I+R\}$	Potential DCs, retailers, and potential RCs nodes

Parameters:

$\tilde{d}_{it}$	Fuzzy demand of retailer i in period t
Ql	Capacity of a lorry
Dpd_d	Distance of the plant to DC d
tt_d	Travel time from the plant to DC d
Ce	CO_2 emission from one-liter fuel consumption
Cl_{dt}	Transportation cost per km for a lorry from plant to DC d in period t
$FCRl^0$ ($FCRl^1$)	Fuel consumption rate of an empty (fully-loaded) lorry per kilometer

wl^0	Weight of an empty lorry
wl^1	Weight of a fully-loaded lorry ($wl^1 = wl^0 + Ql$)
fd_{dgt}	Fixed activation cost of DC d with technology level g in period t
ce_{dg}	Carbon emission of DC d with technology g
Q_d	Maximum capacity of DC d
$[e_{dt}, l_{dt}]$	The soft time window of DC d in period t
$Pe_t(Pl_t)$	Penalty cost for violating the earliest (latest) time of DC's time windows in period t
rp_{dg}	Required number of personnel for DC d with technology g
rp_{rs}	Required number of personnel for RC r with technology s
dp_{ld}	Distance of the personnel in location l from DC d
$\tilde{a}_l$	Desired distance from a DC for personnel in location l stated by a trapezoidal fuzzy number, $\tilde{a}_l = (a_{1l}, a_{2l}, a_{3l}, a_{4l})$
$b_{m'n'}$	Distance of node m' from node n'
tt_{mn}	Time of traveling from node m to node n
φ_{mnt}	Urban traffic risk between nodes m and n in period t
Fv	Fixed cost of hiring a multi-compartment truck
Q_1t	Capacity of the first part of the multi-compartment truck (freezer)
$ECRt^1$	Energy consumption rate of the cooling system of a fully-loaded truck
Q_2t	Capacity of the second part of the multi-compartment truck (without freezer)
$Ct_{m'n't}$	Transportation cost per kilometer for a multi-compartment truck traveled from node m' to node n' in period t
$FCRt^0$ ($FCRt^1$)	Fuel consumption rate of an empty (fully-loaded) multi-compartment truck per kilometer
wt^0	Weight of an empty multi-compartment truck
wt^1	Weight of a fully-loaded multi-compartment truck ($wt^1 = wt^0 + Q_{1t} + Q_{2t}$)
pr_i	Priority coefficient of retailer i
$(\tilde{tw}_{it})$	Desired time window of retailer i in period t by a trapezoidal fuzzy number, $\tilde{tw}_{it} = (tw_{1it}, tw_{2it}, tw_{3it}, tw_{4it})$
h_{it}	Inventory holding cost of retailer i in period t
cap_i	Depot capacity of retailer i
θ	Percentage of perished products that should be disposed
fr_{rst}	Fixed operating cost of RC r with technology level s in period t
ce_{rs}	Carbon emission of RC r with technology s
Q_r	Maximum capacity of RC r
P_t	Selling price of recycled products in the secondary market in period t
bd_r	Distance of RC r to the CDC
Qf	Capacity of a homogeneous fleet
Cf_{rt}	Transportation cost of a fleet from RC r to the CDC in period t
$FCRf^0$ ($FCRf^1$)	Fuel consumption rate of an empty (fully-loaded) fleet per kilometer
wf^0	Weight of an empty homogeneous fleet
wf^1	Weight of a fully-loaded homogeneous fleet ($wf^1 = wf^0 + Qf$)
$rd_d(rd_r)$	Regional development percentage for region d (region r)
if_{dg}	Regional development impact of activated DC d with technology g
if_{rs}	Regional development impact of operated RC r with technology s
M	A large arbitrary number

Variables:

Nl_{dt}	Number of lorries sent from the plant to DC d in period t
Nf_{rt}	Number of homogeneous fleets from RC r to the CDC in period t
Ve_{dt}	Violation amount from e_{dt}, the earliest time of the soft time window of DC d in period t
Vl_{dt}	Violation amount from l_{dt}, the latest time of the soft time window of DC d in period t
V_{dt}	Number of products sent from plant to DC d in period t
at_{it}	Arrival time at retailer i in period t
w_{ldt}	1 if personnel l allocated to DC d in period t; 0, otherwise

y^g_{dt} 1 if DC d with technology g is activated in period t; 0, otherwise

y^s_{rt} 1 if RC r with technology s is operated in period t; 0, otherwise

z_{idt} 1 if retailer i is allocated to DC d in period t; 0, otherwise

yx^t_{ir} 1 if the last retailer i connects to RC r in period t; 0, otherwise

x^t_{mn} 1 if node m connects to node n in period t, $m, n \in \{1, 2, ..., D + I\}$; 0, otherwise

yn_{dt} Auxiliary variable, 1 if $Nl_{dt} > 0$; 0, otherwise (i.e., $Nl_{dt} = 0$)

yf_{rt} Auxiliary variable, 1 if $Nf_{rt} > 0$; 0, otherwise (i.e., $Nf_{rt} = 0$)

u^t_m Deliverable load of a multi-compartment truck before starting to serve node m in period t

uu^t_m Picked load of a multi-compartment truck after serving node m in period t

I_{it} Inventory level of retailer i at the end of period t

qq_{it} Total quantity of received products by retailer i in period t

$q_{itt'}$ Quantity of received products by retailer i in period t for being used in period t'

ex_{it} Quantity of expired products in retailer i at the end of period t

Based on the membership function of the trapezoidal fuzzy number $\tilde{a}_l$, the utility function of personnel l working in DC d, up_{ld}, is defined as follows:

$$up_{ld} = \begin{cases} 0 & dp_{ld} < a_{1l} \text{ or } dp_{ld} > a_{4l} \\ \frac{dp_{ld} - a_{1l}}{a_{2l} - a_{1l}} & a_{1l} \leq dp_{ld} < a_{2l} \\ 1 & a_{2l} \leq dp_{ld} \leq a_{3l} \\ \frac{a_{4l} - dp_{ld}}{a_{4l} - a_{3l}} & a_{3l} < dp_{ld} \leq a_{4l} \end{cases} \tag{1}$$

Similarly, the utility function of retailer i in period t, uc_{it}, is defined as Eq. (2) based on the desired arrival time ($t\tilde{w}_{it}$) stated by experts subjectively:

$$uc_{it} = \begin{cases} 0 & at_{it} < tw1_{it} \text{ or } at_{it} > tw4_{it} \\ \frac{at_{it} - tw1_{it}}{tw2_{it} - tw1_{it}} & tw1_{it} \leq at_{it} < tw2_{it} \\ 1 & tw2_{it} \leq at_{it} \leq tw3_{it} \\ \frac{tw4_{it} - at_{it}}{tw4_{it} - tw3_{it}} & tw3_{it} < at_{it} \leq tw4_{it} \end{cases} \tag{2}$$

3.1. Mathematical formulation

Objective functions:

$$\text{Min} f_1 = \sum_{t=1}^{T} \sum_{d=1}^{D} Nl_{dt} Cl_{dt} Dpd_d$$

$$+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} fd_{dgt} y^g_{dt}$$

$$+ \sum_{t=1}^{T} \sum_{d=1}^{D} (pe_t ve_{dt} + pl_t vl_{dt})$$

$$\sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{i=1}^{I} fvx^t_{di}$$

$$+ \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{n=1}^{M} Ct_{mnt} b_{mn} x^t_{mn}$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{r=1}^{R} Ct_{irt} b_{ir} yx^t_{ir}$$

$$+ \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{s=1}^{S} fr_{rst} y^s_{rt}$$

$$+ \sum_{t=1}^{T} \sum_{r=1}^{R} Nf_{rt} Cf_{rt} bd_r$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{1}{2} h_{it} I_{it} - \sum_{t=1}^{T} \sum_{d=1}^{D} P_t (1 - \theta) uu^t_d, \tag{3}$$

$$\text{Min} f_2 = \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} ce_{dg} y^g_{dt} + \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{s=1}^{S} ce_{rs} y^s_{rt}$$

$$+ \sum_{t=1}^{T} \sum_{d=1}^{D} (1 + ce) Dpd_d FCRl^1 (Nl_t - 1) yn_{dt}$$

$$+ \sum_{t=1}^{T} \sum_{d=1}^{D} ((1 + ce) Dpd_d FCRl^0 yn_{dt}$$

$$+ \left(\frac{FCRl^1 - FCRl^0}{Ql} \right) (V_{dt}$$

$$-Ql(Nl_{dt} - 1) yn_{dt}))$$

$$+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{i=1}^{I} (1 + ce) b_{mi} x^t_{mi} (FCRt^0$$

$$+ \left(\frac{FCRt^1 - FCRt^0}{Q1t + Q2t} \right) (u^t_i + uu^t_{m/\{D\}}))$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{r=1}^{R} (1 + ce) b_{ir} yx^t_{ir} (FCRt^0$$

$$+ \left(\frac{FCRt^1 - FCRt^0}{Q1t + Q2t} \right) (u^t_i + uu^t_i))$$

$$+\sum_{t=1}^{T}\sum_{r=1}^{R}(1+ce)bd_r FCRf_{hf}^1(Nf_{rt}-1)yf_{rt}$$

$$+\sum_{t=1}^{T}\sum_{r=1}^{R}((1+ce)bd_r(FCRf_{hf}^0 yf_{rt}$$

$$+\left(\frac{FCRf_{hf}^1-FCRt_{hf}^0}{Qf}\right)\left(\theta\sum_{i=1}^{I}uu_i^t yx_{ir}^t\right.$$

$$\left.-Qf(Nf_{rt}-1)yf_{rt}\right)$$

$$+\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{i=1}^{I}b_{mi}x_{mi}^t\left(\frac{ECR^1}{Q1t}\right)u_i^t, \tag{4}$$

$$\text{Max}f_3=\alpha_1\sum_{t=1}^{T}\sum_{i=1}^{I}pr_i uc_{it}+\alpha_2\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{l=1}^{L}w_{ldt}up_{ld}$$

$$+\alpha_3\left(\left\{\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{g=1}^{G}y_{dt}^g if_{dg}(1-rd_d)\right.\right.$$

$$\left.+\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{S}y_{rt}^s if_{rs}(1-rd_r)\right\}$$

$$+\left\{\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{g=1}^{G}y_{dt}^g rp_{dg}\right.$$

$$\left.\left.+\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{S}y_{rt}^s rp_{rs}\right\}\right). \tag{5}$$

Constraints:

$$Nl_{dt}\geq V_{dt}/Ql \qquad \forall t\in T,\forall d\in D, \tag{6.1}$$

$$Nl_{dt}\leq V_{dt}/Ql+1 \qquad \forall t\in T,\ \forall d\in D, \tag{6.2}$$

$$V_{dt}\leq Q_d\sum_{g=1}^{G}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D, \tag{7}$$

$$\sum_{g=1}^{G}y_{dt}^g\leq 1 \qquad \forall t\in T,\ \forall d\in D, \tag{8}$$

$$V_{dt}=\sum_{i=1}^{I}y_{dt}^g qq_{it}z_{idt} \qquad \forall t\in T,\ \forall d\in D, \tag{9}$$

$$\sum_{d=1}^{D}z_{idt}=1 \qquad \forall t\in T,\ \forall i\in I, \tag{10}$$

$$\sum_{i=1}^{I}z_{idt}\leq M\sum_{g=1}^{G}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D, \tag{11.1}$$

$$\sum_{g=1}^{G}y_{dt}^g\leq\sum_{i=1}^{I}z_{idt} \qquad \forall t\in T,\ \forall d\in D, \tag{11.2}$$

$$Ve_{dt}\geq(e_{dt}-tt_d)\sum_{g=1}^{G}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D, \tag{12.1}$$

$$Vl_{dt}\geq(tt_d-l_{dt})\sum_{g=1}^{G}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D, \tag{12.2}$$

$$w_{ldt}\leq\sum_{g=1}^{G}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D,\ \forall l\in L, \tag{13}$$

$$\sum_{l=1}^{L}w_{ldt}=\sum_{g=1}^{G}rp_{dg}y_{dt}^g \qquad \forall t\in T,\ \forall d\in D, \tag{14}$$

$$\sum_{m=1}^{M}x_{im}^t=1 \qquad \forall t\in T,\ \forall i\in I, i\neq m, \tag{15}$$

$$\sum_{n=1}^{M}x_{nm}^t=\sum_{n=1}^{M}x_{mn}^t \qquad \forall t\in T,\ \forall m\in M, \tag{16}$$

$$\sum_{d=1}^{D}x_{id}^t uu_i^t\leq M\sum_{r=1}^{R}yx_{ir}^t \qquad \forall t\in T,\ \forall i\in I, \tag{17.1}$$

$$\sum_{r=1}^{R}yx_{ir}^t\leq M\sum_{d=1}^{D}x_{id}^t.uu_i^t \qquad \forall t\in T,\ \forall i\in I, \tag{17.2}$$

$$\sum_{r=1}^{R}yx_{ir}^t\leq 1 \qquad \forall t\in T,\ \forall i\in I, \tag{17.3}$$

$$\sum_{i=1}^{I}yx_{ir}^t\leq M\sum_{s=1}^{S}y_{rt}^s \qquad \forall t\in T,\ \forall r\in R, \tag{18.1}$$

$$\sum_{s=1}^{S}y_{rt}^s\leq\sum_{i=1}^{I}yx_{ir}^t \qquad \forall t\in T,\ \forall r\in R, \tag{18.2}$$

$$\sum_{s=1}^{S}y_{rt}^s\leq 1 \qquad \forall t\in T,\ \forall r\in R, \tag{19}$$

$$x_{id}^t\leq z_{idt} \qquad \forall t\in T,\ \forall i\in I,\ \forall d\in D, \tag{20}$$

$$x_{di}^t\leq z_{idt} \qquad \forall t\in T,\ \forall i\in I,\ \forall d\in D, \tag{21}$$

$$x_{ij}^t+z_{idt}+\sum_{\substack{d=1\\ d\neq d'}}^{D}z_{jd't}\leq 2$$

$$\forall t\in T,\ \forall i,j\in I, i\neq j,\ \forall d\in D, \tag{22}$$

$$\sum_{i=1}^{I} uu_i^t yx_{ir}^t \leq Q_r \sum_{s=1}^{S} y_{rt}^s \qquad \forall t \in T,\ \forall r \in R, \tag{23}$$

$$u_j^t - u_i^t + x_{ij}^t Q1t + (Q1t - qq_{it} - qq_{jt}) x_{ji}^t \leq Q1t - qq_{it} \quad \forall t \in T,\ \forall i,j \in I, i \neq j, \tag{24}$$

$$uu_i^t - uu_j^t + x_{ij}^t Q2t + (Q2t - ex_{it} - ex_{jt}) x_{ji}^t \leq Q2t - ex_{jt}, \quad \forall t \in T,\ \forall i,j \in I, i \neq j, \tag{25}$$

$$u_i^t \leq Q1t - (Q1t - qq_{it}) \sum_{d=1}^{D} x_{id}^t \qquad \forall t \in T,\ \forall i \in I, \tag{26}$$

$$uu_i^{2bt} \leq Q2t - (Q2t - ex_{it}) \sum_{d=1}^{D} x_{di}^t \qquad \forall t \in T,\ \forall i \in I, \tag{27}$$

$$u_d^t = \sum_{i=1}^{I} z_{idt} qq_{it} u_d^t \qquad \forall t \in T,\ \forall d \in D, \tag{28}$$

$$uu_d^t = \sum_{i=1}^{I} z_{idt} ex_{it} \qquad \forall t \in T,\ \forall d \in D, \tag{29}$$

$$qq_{it} + \sum_{\substack{j=1 \\ i \neq j}}^{J} x_{ij}^t qq_{jt} \leq u_i^t \qquad \forall t \in T,\ \forall i \in I, \tag{30}$$

$$ex_{it} + \sum_{\substack{j=1 \\ i \neq j}}^{J} x_{ij}^t ex_{jt} \leq uu_i^t \qquad \forall t \in T,\ \forall i \in I, \tag{31}$$

$$at_{it} + M(1 - x_{di}^t) \geq tt_{di}(1 + \varphi_{dit}) \quad \forall t \in T,\ \forall i \in I,\ \forall d \in D, \tag{32.1}$$

$$at_{it} - M(1 - x_{di}^t) \leq tt_{di}(1 + \varphi_{dit}) \quad \forall t \in T,\ \forall i \in I,\ \forall d \in D, \tag{32.2}$$

$$at_{jt} + M(1 - x_{ij}^t) \geq at_{it} + tt_{ij}(1 + \varphi_{ijt}) \quad \forall t \in T,\ \forall i \in I,\ \forall j \in I, \tag{33.1}$$

$$at_{jt} - M(1 - x_{ij}^t) \leq at_{it} + tt_{ij}(1 + \varphi_{ijt}) \quad \forall t \in T,\ \forall i \in I,\ \forall j \in I, \tag{33.2}$$

$$Nf_{rt} \geq \theta \sum_{i=1}^{I} uu_i^t yx_{ir}^t \Big/ Qf \qquad \forall t \in T,\ \forall r \in R, \tag{34.1}$$

$$Nf_{rt} \leq \theta \sum_{i=1}^{I} uu_i^t yx_{ir}^t \Big/ Qf + 1 \qquad \forall t \in T,\ \forall r \in R, \tag{34.2}$$

$$I_{it} = I_{it-1} + qq_{it} - \widetilde{d_{it}} - ex_{it} \qquad \forall t \in T,\ \forall i \in I, \tag{35}$$

$$qq_{iy} \leq cap_i - I_{it-1} \qquad \forall t \in T,\ \forall i \in I, \tag{36.1}$$

$$I_{it} \leq cap_i \qquad \forall t \in T,\ \forall i \in I, \tag{36.2}$$

$$q_{itt'} \leq cap_i \qquad \forall t \in T,\ \forall i \in I, \tag{36.3}$$

$$Ex_{it} = \sum_{k=t}^{T} q_{i(t-sl)k} \qquad \forall t \in T,\ \forall i \in I, t \geq SL, \tag{37.1}$$

$$Ex_{it} = 0 \qquad \forall t \in T,\ \forall i \in I, t \leq SL, \tag{37.2}$$

$$\sum_{t'=1}^{T} q_{itt'} = qq_{it} \qquad \forall t \in T,\ \forall i \in I, \tag{38}$$

$$\sum_{t' \leq t}^{T} q_{itt'} = 0 \qquad \forall t \in T,\ \forall i \in I, \tag{39}$$

$$Nl_{dt} \leq Myn_{dt} \qquad \forall t \in T,\ \forall d \in D, \tag{40}$$

$$Nf_{rt} \leq Myf_{rt} \qquad \forall t \in T,\ \forall r \in R, \tag{41}$$

$$y_{dt}^g, y_{rt}^s, w_{ldt}, z_{idt}, x_{mn}^t, yx_{ir}^t, yn_{dt}, yf_{rt} \in \{0,1\},$$
$$Nl_{dt}, Nf_{rt} \in Z_+ \qquad \text{on other domain},$$
$$V_{dt}, ve_{dt}, vl_{dt}, at_{it}, u_i^t, uu_i^t, I_{it}, q_{itt'}, qq_{it}, Ex_{it} \geq 0. \tag{42}$$

The first objective function minimizes the cost of transportation by lorries from plant to DCs in the outskirts, activating DCs with specified technology levels, violation of DC time windows, hiring of multi-compartment trucks, multi-compartment truck transportation to/between retailers and to RCs, operating RCs, transportation of homogenous fleet to the CDC, and retailers' inventory holding minus the revenue of new products sold to the secondary market.

The second objective function minimizes environmental side effects including CO_2 emission of activating/operating DCs /RCs, FCR, and CO_2 emission of lorries, multi-compartment trucks, and homogeneous fleet. FCR of and CO_2 emission from vehicles are formulated based on the traveled distance and weight of the carried loads. Xiao et al. [43] plotted real data and calculated the FCR of fully-loaded and unloaded trucks per kilometer. In Eq. (4), the FCR of partially-loaded multi-compartment trucks was computed with linear interpolation by considering the summation of two variables, deliverable load (u_m^t) and picked up load (uu_m^t).

The third objective function maximizes the utility of three main network stakeholders. A coefficient is assigned to each stakeholder that can be changed based on the prioritization of the company. The utility of retailers (customers) is formulated as the satisfaction level of service time in comparison to their desired time stated by fuzzy numbers. However, the utility of personnel is defined based on the distance of personnel from assigned DCs (Eq. (1)). The social objective function includes the social and economic impacts of activating/operating a DC/RC with a specified technology level on economic development and job creation.

Constraints (6.1) and (6.2) specify the number of lorries moving from plant to active DCs. Constraint (7) avoids exceeding the capacity level of DCs in each period. Constraint (8) ensures that a DC can work with only one technology level. Constraint (9) calculates the demand assigned to an active DC. Constraint (10) vouches that each retailer be assigned to only one DC. Constraints (11.1) and (11.2) impose that a DC can be activated if there is a retailer assigned to it. Constraints (12.1) and (12.2) calculate the violation of the earliest and latest DC time windows, respectively. Constraint (13) states that only if a DC is activated, personnel can be allocated to it. Constraint (14) maintains the number of allocated personnel to a DC under maximum required personnel. Constraint (15) shows that each retailer should be connected to one of the retailers/ DCs. The flow balance of each node is guaranteed by Eq. (16). Constraints (17.1) to (17.3) assign operated RCs to the last retailer of routes if any expired products are loaded on the multi-compartment truck. If no expired product was picked up by trucks, the route would be open without assigning to RCs.

Constraints (18.1) and (18.2) impose that an RC can be active if there is a truck visiting it. Constraint (19) ensures that an RC is activated with just one technology level. Constraints (20)–(22) prevent the creation of unauthorized routes. The Location Routing Problem with Simultaneous Pickup and Delivery (LRPSPD) is subject to structural constraints. If a retailer is allocated to DC d, it can be the last retailer of a route linked to DC d by a dummy arc (Constraint (20)), or the first retailer in a route starting from DC d (Constraint (21)); or be connected to other retailers that are allocated to the same DC (Constraint (22)). Constraint (23) ensures the capacity limitation of RCs. Constraints (24) and (25) state the imbalance of delivery and pick-up flows between two nodes.

Constraints (26) and (27) mandate the remaining load of each compartment of trucks at each node. Also, Constraints (24) and (26) ascertain that fresh load be under the capacity of the compartment with cooling equipment. Constraints (25) and (27) put the second compartment capacity limitation on the amount of picked up expired products. Constraint (28) determines the fresh products needed at each active DC. Constraint (29) calculates the number of expired products gathered from all retailers, which are allocated to the same DC. Constraints (24) to (31) determine the limitations of auxiliary variables u_i^t and uu_i^t.

Constraints (32.1) and (32.2) calculate the arrival time at the first retailer along each route. Constraints (33.1) and (33.2) calculate the arrival time at other retailers. The number of the needed homogenous fleet for transferring unusable perished products to the CDC is calculated by Constraints (34.1) and (34.2). For each retailer, Constraint (35) balances among the inventory levels of the current and previous period, the demand, received products, and expired products of the current period. Constraints (36.1), (36.2), and (36.3) ensure that the inventory level of a retailer does not exceed its capacity level. The number of expired products is calculated by Constraints (37.1) and (37.2) based on the violation of holding duration from the product's shelf life. Constraint (38) calculates the total quantity of received products by each retailer periodically. Constraint (39) prohibits back-ordering demands to avoid customer dissatisfaction. Constraints (40) and (41) determine variables yn_{dt} and yf_{rt} based on their definition. Finally, Constraint (42) determines the variable's domain.

3.1.1. Linearization of multiplying a binary variable by a continuous variable

This multiplicative statements appeared in the objective functions (e.g., $Nl_{dt}.yn_{dt}$ and $Nf_{rt}.yf_{rt}$ in Eq. (4) and, also, some constraints (e.g., (9), (17.1), (23), (24), (25), (26), (27), (29), (30), (34.1), and (34.2)). If a continuous variable (Q) is multiplied by a binary variable (x), the multiplicative statement should be replaced by a new continuous variable y (i.e., $y = Qx$) and the following constraints should be added to the model:

$$y \leq Q \leq Mx, \tag{43.1}$$

$$y \leq Mx, \tag{43.2}$$

$$y \geq Q - M(1-x), \tag{43.3}$$

$$Q \geq 0, \quad x \in \{0,1\}, \quad y \geq 0.$$

3.1.2. Linearization of multiple breakpoint functions

Regarding the fuzzy desired time window of retailer i in period t, $t\widetilde{w}_{it}$, the utility function of retailer i in period t, uc_{it}, can be stated as a piecewise linear function of arrival time, at_{it}, as follows:

$uc_{it} =$

$$\begin{cases} 0 & at_{it} < tw1_{it} or at_{it} > tw4_{it} \\ \frac{at_{it}}{tw2_{it} - tw1_{it}} - \frac{tw1_{it}}{tw2_{it} - tw1_{it}} & tw1_{it} \leq at_{it} < tw2_{it} \\ 1 & tw2_{it} \leq at_{it} \leq tw3_{it} \\ \frac{tw4_{it}}{tw4_{it} - tw3_{it}} - \frac{at_{it}}{tw4_{it} - tw3_{it}} & tw3_{it} < at_{it} \leq tw4_{it} \end{cases} \quad (44)$$

According to Al-e-hashem et al. [44], by defining a continuous variable $att_{bp\ it}$ and a binary variable bb_{bp}, where index bp shows each linear piece of the utility function, the multiple breakpoint functions (44) can be converted into the following single function:

$$uc_{it} = att_{2it} \frac{1}{tw2_{it} - tw1_{it}} - bb_2 \frac{tw1_{it}}{tw2_{it} - tw1_{it}}$$
$$+ bb_3 \times 1 - att_{4it} \frac{1}{tw4_{it} - tw3_{it}}$$
$$+ bb_4 \frac{tw4_{it}}{tw4_{it} - tw3_{it}}. \quad (45)$$

Also, the following equations should be added to the model:

$$-Mbb_1 \leq att_{1it} \leq tw1_{it} bb_1 \qquad \forall t \in T, \forall i \in I, \quad (46.1)$$

$$tw1_{it} bb_2 \leq att_{2it} \leq tw2_{it} bb_2 \qquad \forall t \in T, \forall i \in I, \quad (46.2)$$

$$tw2_{it} bb_3 \leq att_{3it} \leq tw3_{it} bb_3 \qquad \forall t \in T, \forall i \in I, \quad (46.3)$$

$$tw3_{it} bb_4 \leq att_{4it} \leq tw4_{it} bb_4 \qquad \forall t \in T, \forall i \in I, \quad (46.4)$$

$$tw4_{it} bb_5 \leq att_{5it} \leq Mbb_5 \qquad \forall t \in T, \forall i \in I, \quad (46.5)$$

$$\sum_{bp=1}^{BP} att_{bpit} = at_{it} \qquad \forall t \in T, \forall i \in I, \forall d \in D, \quad (46.6)$$

$$\sum_{bp=1}^{BP} bb_{bp} = 1, \quad (46.7)$$

$$bb_{bp} \in \{0, 1\}, att_{bpit} \geq 0 \quad \forall t \in T, \forall i \in I, \forall bp \in BP.$$

Other multi breakpoint linear functions in the developed mathematical model (e.g., the utility of personnel) can be converted into a single linear statement similarly.

3.2. Dealing with fuzzy uncertainty

Because of the competitive market, demand is vague and uncertain. Since no distributional data is available in many cases, demand is stated by a trapezoidal fuzzy number, i.e., $\tilde{d_{it}} = (d_{it_{(1)}}, d_{it_{(2)}}, d_{it_{(3)}}, d_{it_{(4)}})$. Here, the Basic Possibilistic Chance-Constrained Programming (BPCPP) approach is applied for defuzzification. Regarding BPCPP, the expected value is used for uncertain parameters in the objective function. To transform constraints to crisp statements, the necessity measure (Nec) is applied [45]. Constraint (35) is replaced with two inequalities below:

$$Nec\{I_{it} \leq I_{it-1} + qq_{it} - \widetilde{d_{it}} - ex_{it}\} \geq \beta$$
$$\forall t \in T, \forall i \in I, \quad (47.1)$$

$$Nec\{I_{it} \geq I_{it-1} + qq_{it} - \widetilde{d_{it}} - ex_{it}\} \geq \beta$$
$$\forall t \in T, \forall i \in I, \quad (47.2)$$

where $0.5 < \beta < 1$ is the minimum confidence level of chance constraints. Finally, the two above constraints are replaced with Constraints (48.1) and (48.2) as follows:

$$I_{it} \leq I_{it-1} + qq_{it} - ((1-\beta) d_{it_{(2)}} + \beta d_{it_{(1)}}) - ex_{it}$$
$$\forall t \in T, \forall i \in I, \quad (48.1)$$

$$I_{it} \geq I_{it-1} + qq_{it} - ((1-\beta) d_{it_{(3)}} + \beta d_{it_{(4)}}) - ex_{it}$$
$$\forall t \in T, \forall i \in I. \quad (48.2)$$

In the rest of this study, β is set to 0.8.

4. Solution approach

In this section, the developed model is first solved by the exact method. The multi-objective model is turned into a single-objective one by the TH method [46]. Then, two meta-heuristics are developed to find near-optimal solutions in a reasonable time, especially for medium- and large-sized cases.

Ahmadi Javid and Azad [32] found that the LRIP, which is a simple form of the model presented in Section 3, belonged to the NP-complete class with a non-polynomial order of solving time, without considering backward flow, recycling stage, and product shelf life. Devika et al. [5] also formulated a CLSC that could be a sub-problem of our model without perishability and some decision levels, and acknowledged the NP-completeness of the studied problem. Thus, the LRIP model considered in this paper is classified as an NP-complete problem since it is a comprehensive version of the problems mentioned above. Because of the long solving time of the exact method, two meta-heuristics namely Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) and a hybrid multi-objective algorithm are developed and compared based on the multi-objective performance metrics to deal with the problem in a reasonable solving time. Moreover, some heuristic procedures are tailored for solution representation to achieve a feasible solution by taking all constraints into account. A core i7 laptop does all computations with 12 GB RAM and 2.6 GHz CPU on a 64-bit Windows.

4.1. Model validation and application

The developed model is solved by CPLEX solver of GAMS software version 24.8.3 as powerful software in solving MILP problems. For model validation, it is implemented for a real-case study. There is an industrial bread plant in a neighboring city of Tehran. There are two DCs in the outskirt for unloading products from big lorries to smaller two-compartment trucks. There are five retailers in the city. Two RCs in the city are ready to recycle expired products. The DCs and RCs should decide on their applied technology to be solar or electricity. The planning horizon is three periods. Therefore, the size of the case study is $|D| \times |G| \times |I| \times |R| \times |S| \times |L| \times |T| = 2 \times 2 \times 5 \times 2 \times 2 \times 10 \times 3$. The extent of other parameters is stated in Subsection 4.6 used for generating test problems.

The three single-objective problems by each objective function are solved for showing the conflict among three objective functions [11]. The results of these problems are reported in Table 3. In this table, retailers are shown by numbers 3 to 7. The first part of the table shows the optimal solution obtained in the presence of the economic objective function. In this case, because of selling secondary products, a significant number of expired products are delivered to the RCs. Moreover, a limited number of DCs and RCs are opened with a cheap technology level even though this technology level has high environmental side effects. Activation of a few DCs/RCs prevents job creation through opening DCs/RCs. Therefore, the supply chain is planned without attention to its environmental and social impacts.

In the second part of Table 3, when the problem is solved in the presence of the green objective function,

Table 3. Optimal solution of the case study by considering only one objective function.

	Period	Plant	NL	DC	Order of retailers in a route	RC	Nf	CDC
Objective function 1	1	1	1	1✓ {g=2}	$1 \gg 5 > 3 > 4 \gg 1$ $1 \gg 7 > 6 \gg 1$	1	–	1
			–	2	–	2	–	
	2	1	1	1✓ {g=2}	$1 \gg 4 > 3 > 7 \gg 1$ $1 \gg 5 > 6 \gg 1$	1	–	1
			–	2	–	2	–	
	3	1	1	1✓ {g=2}	$1 \gg 4 > 3 > 7 \gg$(RC:1) $1 \gg 5 > 6 \gg$(RC:1)	1✓ {s=2}	1	1
			–	2	–	2	–	
Objective function 2	1	1	1	1✓ {g=1}	$1 \gg 5 > 4 \gg 1$	1	–	1
			1	2✓ {g=1}	$2 \gg 6 > 7 > 3 \gg 2$	2	–	
	2	1	1	1✓ {g=1}	$1 \gg 7 > 6 > 5 \gg 1$	1	–	1
			1	2✓ {g=1}	$2 \gg 4 > 3 \gg 2$	2	–	
	3	1	1	1✓ {g=1}	$1 \gg 5 > 6 > 7 > 3 > 4 \gg 1$	1	–	1
			–	2	–	2	–	
Objective function 3	1	1	1	1✓ {g=1}	$1 \gg 7 > 6 \gg 1$	1	–	1
			1	2✓ {g=1}	$2 \gg 3 > 4 > 5 \gg 2$	2	–	
	2	1	1	1✓ {g=1}	$1 \gg 7 > 6 \gg 1$	1	–	1
			1	2✓ {g=1}	$2 \gg 3 > 4 > 5 \gg 2$	2	–	
	3	1	1	1✓ {g=1}	$1 \gg 7 \gg$(RC:2)	1✓ {s=1}	1	1
			1	2✓ {g=1}	$2 \gg 3 > 6 > 4 > 5 \gg$(RC:1)	2✓ {s=1}	1	

there is no need to store excessive products and then, sell expired products to the RCs, which cause GHG emissions. Plus, DCs utilizes nature-friendly technology; however, it is expensive.

Based on the last part of Table 3, which shows the optimal solution in the presence of only the social objective function, most of the DCs/RCs are operated. However, it is costly and may not be environment-friendly; it causes job creation and economic growth in the local regions. In this case, the length of the routes is more uniform because of emphasizing the time windows of the retailers. In this table, the distinction among optimal solutions by considering different goals confirms the conflict of goals. Therefore, the necessity of considering different objective functions simultaneously and solving a multi-objective problem is verified.

4.2. Turning the multi-objective problem to a single one by the TH method

One of the main methods for solving MOPs that gives efficient balanced and unbalanced solutions is the TH method [46]. This method is a fuzzy-based method that deals with the MOP in a way that maximizes the satisfaction degree of objective functions [41]. After determining the Positive Ideal Solution (PIS), (f_i^{PIS}, x_i^{PIS}), and the Negative Ideal Solution (NIS), (f_i^{NIS}, x_i^{NIS}), the satisfaction degree of a minimization objective function is calculated by:

$$\mu_i(x) = \begin{cases} 1 & \text{If} \quad f_i < f_i^{PIS} \\ \frac{f_i^{NIS} - f_i}{f_i^{NIS} - f_i^{PIS}} & \text{If} \quad f_i^{PIS} \leq f_i \leq f_i^{NIS} \\ 0 & \text{If} \quad f_i > f_i^{NIS} \end{cases} \tag{49}$$

The satisfaction degree for maximization objective functions is formulated as Eq. (50):

$$\mu_i(x) = \begin{cases} 1 & \text{If} \quad f_i > f_i^{PIS} \\ \frac{f_i - f_i^{NIS}}{f_i^{PIS} - f_i^{NIS}} & \text{If} \quad f_i^{NIS} \leq f_i \leq f_i^{PIS} \\ 0 & \text{If} \quad f_i < f_i^{NIS} \end{cases} \tag{50}$$

In the developed model, three objective functions are targeted. The values of the PIS are reported by solving three single objective problems in Table 4 (pay-off table), while the values of the NIS are specified to be approximate that result from having more than two objective functions.

After determining $\mu_i(x)$ for all objectives, the aggregate function of the TH method for turning MOP into a single-objective problem is formulated by:

$$\text{Max} \varphi \beta_0 + (1 - \varphi) \sum\nolimits_k \theta_k \mu_k(x), \tag{51}$$

$$\mu_k(x) \geq \beta_0 \qquad \forall k, x \in F_x, \tag{52}$$

where $\beta_0 \in [0, 1]$ and $\beta_0 = \{\mu_k(x)\}$. φ is the coefficient of compensation, which controls the minimum satisfaction level of the objectives (β_0) besides the compromise degree among the objectives. Moreover, θ_k shows the relative importance of the kth objective function determined by the decision-maker based on the preferences such that $\sum_k \theta_k = 1$, $\theta_k > 0$.

The optimal solution of the TH method for $\theta_1 = 0.4$, $\theta_2 = 0.2$, $\theta_3 = 0.4$, $\varphi = 0.55$ is reported in Table 5. To show the solution better, a schematic view is also presented in Figure 2.

Table 4. Pay-off table.

x_i^*	Desired orientation of f_i	f_1	f_2	f_3
x_1^*	Min f_1	$f_1^{PIS^*} = 7254.767$	$f_2(x_1^*) = 6449.520$	$f_3(x_1^*) = 30.2386$
x_2^*	Min f_2	$f_1(x_2^*) = 12056.5$	$(f_2^{PIS})^* = 4668.214$	$f_3(x_2^*) = 38.7702$
x_3^*	Max f_3	$f_1(x_3^*) = 18261.3$	$f_2(x_3^*) = 10449.519$	$(f_3^{PIS})^* = 59.952$
f_i^{NIS}	Max$\{f_{1,2}(x^*)\}$ Min$\{f_3(x^*)\}$	18261.3	10449.519	30.2386

Table 5. Optimal solution of the case study by the TH method, $\theta_1 = 0.4$, $\theta_2 = 0.2$, $\theta_3 = 0.4$, $\varphi = 0.55$.

Period	Plant	NL	DC	Order of retailers in a route	RC	Nf	CDC
1	1	1	1✓ {g=1}	$1 \gg 4 > 6 \gg 1$ $1 \gg 5 > 7 > 3 \gg 1$	1	–	1
		–	2	–	2	–	
2	1	1	1✓ {g=1}	$1 \gg 3 > 7 \gg 1$ $1 \gg 5 > 6 > 4 \gg 1$	1	–	1
		–	2	–	2	–	
3	1	1	1✓ {g=1}	$1 \gg 4 > 3 > 7 \gg$(RC:1) $1 \gg 5 > 6 \gg$(RC:1)	1✓ {s=1}	1	1
		–	2	–	2	–	

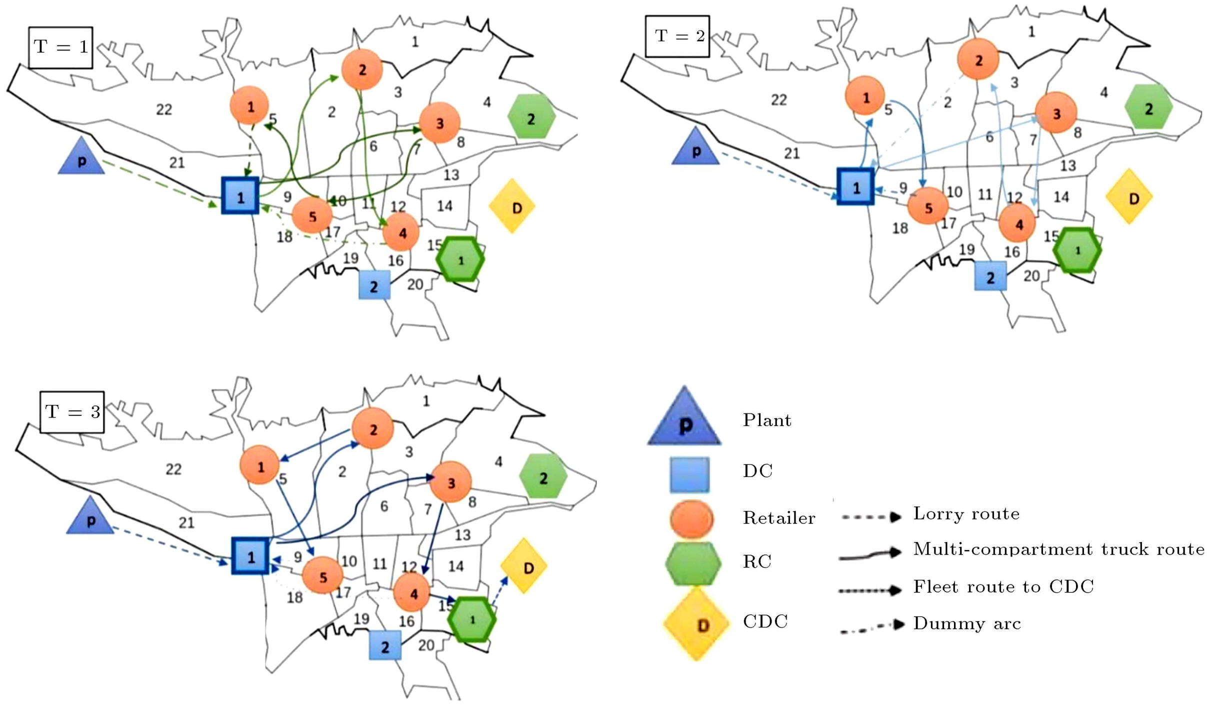

Figure 2. Solution obtained by the TH method for $\varphi = 0.55$.

Table 6. Pareto-optimal solutions of the TH method.

	φ	Objective 1	Objective 2	Objective 3	Satisfaction degree	Computational time
$2\times2\times5\times2\times2\times10\times3$	0.55	10518.43	6362.177	67.9	$\mu_T(f) = 0.805$	14400
	0.65	10178.19	6193.62	61.03	$\mu_T(f) = 0.788$	14550
	0.75	9837.953	6025.061	54.166	$\mu_T(f) = 0.769$	14500
	0.85	9830.153	6020.403	53.661	$\mu_T(f) = 0.767$	14250
	0.95	9820.352	6015.816	53.156	$\mu_T(f) = 0.767$	14300
Avg.		10037.02	6123.415	57.9726	0.7794	14400

The Pareto solutions are obtained by different values of φ, including 0.55, 0.65, 0.75, 0.85, 0.95, presented in Table 6. As shown in the last column of this table, the computation time of the exact method for even a small problem is very long, let alone the medium- or large-sized ones. Even the time required for estimating f_i^{NIS}, which is necessary for the TH method, is ignored in the calculation. Therefore, two meta-heuristic algorithms are developed.

4.3. Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

NSGA-II is a population-based meta-heuristic algorithm [47] that finds a set of non-dominated solutions (called a Pareto front) using specific sorting and selection methods. Due to the domination concept, x dominates y if and only if in all objectives, x is not worse than y and at least in one of the objectives, x is better than y [47]. The steps of the NSGA-II procedure are as follows:

Phase 1: Initialization:

Step 1. Generating the initial population;

Step 2. Calculating fitness (objective) functions for each solution;

Step 3. Assigning a rank to each chromosome based on the concept of domination for sorting purposes. For sorting chromosomes with the same rank, a *Crowding Distance* (CD) measure, which declares an estimate of the solution's density surrounding a specific solution, is used. CD is equal to the average distance of two neighboring solutions of a specific solution. CD measure prefers the uniformly spread of solutions in the objective space and prioritizes solutions with lower crowding distance. After sorting, the best solutions will be selected as parents by selection methods.

Phase 2: Main loop:

Step 1. Employing the crossover operator with crossover rate, P_c, and the mutation operator with mutation rate, P_m; the next population, Q_t, called offspring population with size N is generated;

Step 2. Combining the offspring with parents organizes the union population R_t;

Step 3. Calculating the fitness value of the union population R_t;

Step 4. Applying non-dominated sorting concerning domination and crowding distance criteria, in order. The first N solutions from the sorted union population R_t are selected as the best solutions to form the population P_{t+1} at the next iteration.

The above steps will be accomplished until reaching the stopping criterion.

4.4. *A new hybrid multi-objective meta-heuristic algorithm*

The NSGA-II does not have a memory to take advantage of the learning. Thus, a new hybrid algorithm is developed by combining the NSGA-II with Multi-Objective Particle Swarm Optimization (MOPSO), which has memory and self-learning ability [48].

The Particle Swarm Optimization (PSO) algorithm for single-objective problems is inspired by the movement of folk birds for finding food. In 2006, the multi-objective version of PSO, named MOPSO, was proposed by Reyes-sierra and Coello [48]. In this population-based algorithm, each particle (equivalent to the chromosome of NSGA-II), uses its personal best memory (x_{pbest}) and global best memory (x_{gbest}) of the swarm to find the best movement for the flight route. It means that each particle uses the knowledge of personal and group intelligence for learning.

The velocity of each particle p for the ith dimension at iteration t, $v_{pi}(t)$, is calculated by:

$$v_{pi}(t) = wv_{pi}(t-1) + c_1 r_1 (x_{pbest}(t) - x_{pi}(t)) + c_2 r_2 (x_{gbest}(t) - x_{pi}(t)), \quad (53)$$

where x_{pbest} is the personal best position of a particle so far and x_{gbest} is the position of the best group (swarm) particle. w is the inertia weight that maintains the impact of the last velocity on the new velocity. C_1 and C_2 are cognitive and social learning coefficients associated with the particle success and neighborhood success, respectively, to handle their influence on the new velocity. r_1 and r_2 are random numbers on [0, 1]. The position of each particle p for the ith dimension at iteration t, $x_{pi}(t)$, is calculated by:

$$x_{pi}(t) = x_{pi}(t-1) + v_{pi}(t). \quad (54)$$

With these explanations, the hybridization process can be illuminated, in which the NSGA-II and MOPSO are integrated hierarchically, as shown in Figure 3. The NSGA-II is first run and, then, the

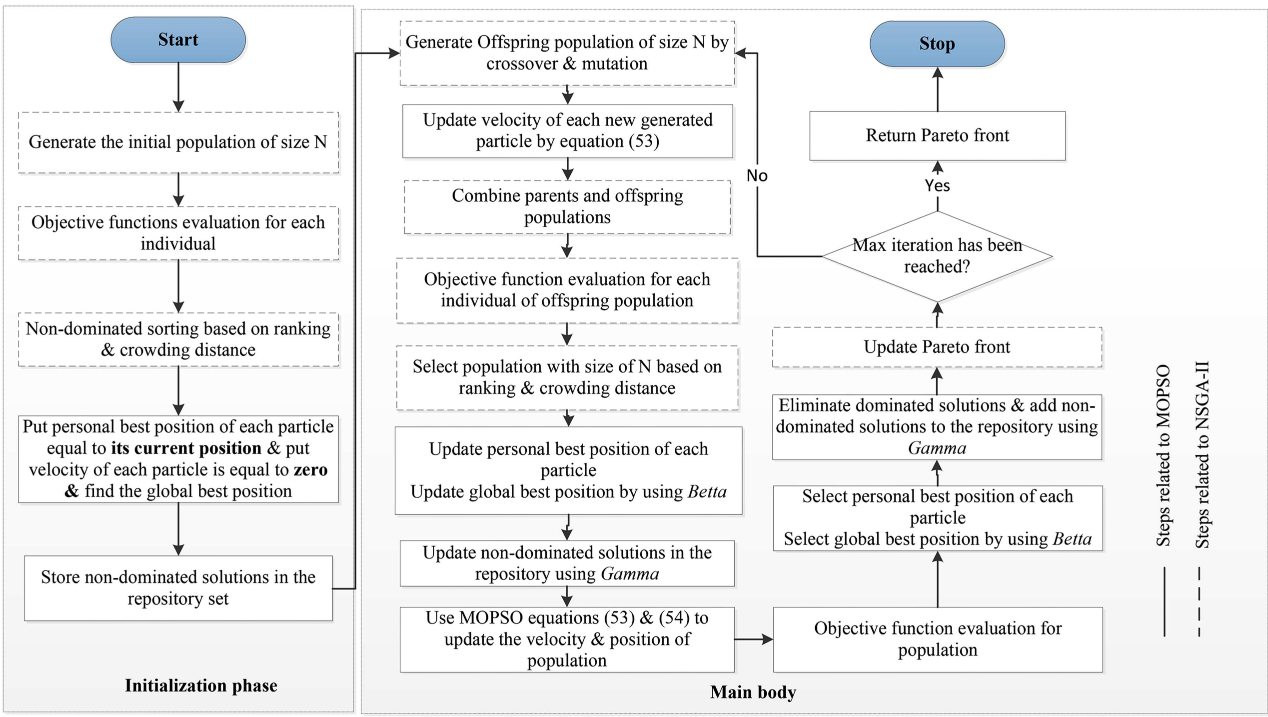

Figure 3. Proposed hybrid NSGA-II-MOPSO algorithm.

solutions are imported to the MOPSO algorithm as an initial swarm to be improved by it.

The initialization phase: The initial population is generated using NSGA-II. The non-dominated solutions are determined by the NSGA-II set as initial particles of MOPSO. Then, the personal best positions and velocities of initial solutions are set to their current position and zero, in order. Finally, the non-dominated solutions are saved in a repository set of MOPSO as initial repository members.

The main body: The main loop starts with the NSGA-II. After generating offspring by crossover and mutation operators, the velocity of each generated solution is updated. Then, the union population is formed and ranked based on domination and CD criteria. The resulting non-dominated population will be the input of the MOPSO algorithm. The best position of each particle is selected as the personal best position. The best position of non-dominated solutions as leaders of the swarm is selected as the global best position. If the number of non-dominated solutions is more than the capacity of the repository, the *Beta* parameter is used as a leader selection pressure [48] to choose leaders from the repository. Then, the steps of the MOPSO algorithm run sequentially. The velocity vector of each particle and its position will be updated by Eqs. (53) and (54), respectively. Afterward, the fitness of each swarm particle is evaluated, and new non-dominated solutions are added to the repository of non-dominated solutions. Subsequently, dominated solutions are eliminated to amend the repository set. If the number of candidate particles for saving in the repository is more than the capacity of the repository, the *Gamma* parameter is used as a deletion pressure. Finally, a new iteration will start if the stopping criterion is not satisfied.

4.5. Initial solution representation

This study attempts to find feasible solutions from the beginning. Since the model has several categories of decision variables, several representation codes, including matrixes/cell arrays, are used to generate the initial solution.

- **The first matrix:** $|T| \times |N + D - 1|$ matrix is used to determine the open DCs and allocate retailers to them. For each period (each row), the matrix is filled with a permutation of the number of retailers and DCs minus one. How to extract activated DCs and assign retailers to them is visible in two steps given in Figure 4.

  The capacity allocated to each active DC should be controlled periodically, which is equal to the total demand of retailers allocated to that DC. The number of trucks needed to deliver the products from the plant to DCs (Nl_{dt}) is derived from the division of assigned capacity to the truck capacity and rounding up the quotient. It is possible to calculate the violation penalty of the soft time windows (Ve_{dt},Vl_{dt}) for each DC by identifying operated DCs and traveling time from the plant to them.

- **The second matrix:** To decide on the technology applied in each DC, a matrix of $1 \times |D|$, filled with integers from [1, G (the number of technology levels for DCs)] is randomly produced, as demonstrated in Figure 5. Thus, the binary variables y^g_{dt} can be specified.

  Now, by considering the demand of assigned retailers to a DC as well as the capacity of the refrig-

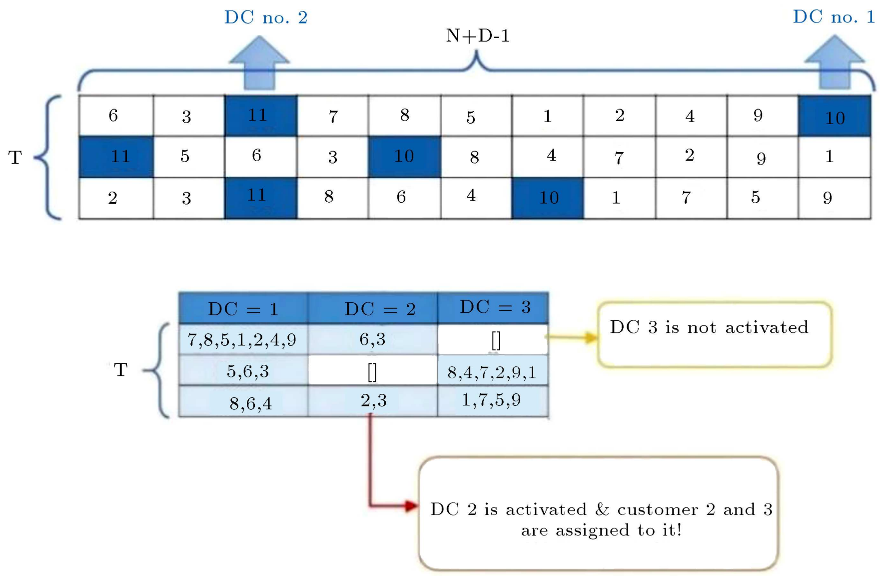

Figure 4. First matrix to present a solution.

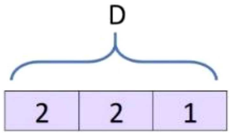

Figure 5. Second matrix to select the DC's technology.

erated and normal part of the multi-compartment truck, the routes beginning from each DC can be determined via the pseudo-code presented in Figure 6.

By identifying the routes, it is easy to calculate the arrival time at each retailer (at_{it}).

- **The third matrix with changing number of columns (cell array):** If a truck carries expired products at the end of an open route, the route should be connected to RC. For this purpose, a cell array of $|T| \times |nT|$ is used where nT shows the number of routes formed in period T. Since nT may vary over periods, cell arrays are used instead of a matrix. The cell array is randomly filled with integers from [1, R], as shown in Figure 7.

  To maintain the feasibility of the solution, the capacity assigned to each operated RC in each period is calculated continuously. As long as the allocated capacity is more than the predetermined capacity of RC, it continues to generate that row of cell arrays randomly. Whenever the last retailer in a route and the RC assigned to it are specified, the binary variables yx^t_{ir} can be determined.

- **The fourth matrix:** To decide on the technology used in each RC, a matrix of $1 \times |R|$ is considered filled by integers from [1, S (the number of technology levels for RCs)] randomly. An example is shown in Figure 8. Therefore, the binary variables y^s_{rt} can be specified.

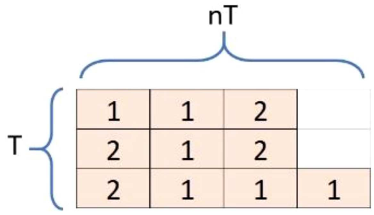

Figure 7. Third cell array to connect eligible routes to RCs.

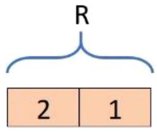

Figure 8. Fourth matrix to select the RC's technology.

  The number of expired products shipped to each RC is determined. By dividing θ% by the fleet capacity, the number of required fleets, Nf_{rt}, to transfer unusable products from an operated RC to the CDC is obtained.

- **The fifth matrix:** To allocate personnel to active DCs, first personnel numbers are put on a permutation matrix for each period. Then, it starts with the first active DC and assigns the first rp_{dg} cells of the matrix to that DC. Similarly, the personnel required for other active DCs are allocated. The matrix with the size of $|T| \times |L|$ is used for this process shown in Figure 9. In this way, the binary variables w_{ldt} can be determined.

Random numbers are applied to determine inventory decision variables. Before generating the matrices

```
For each period ( t=1:T)
    For each active DC:
     Build route nT:
     Pick the first retailer who is not allocated to a route
     Update load of fresh products & load of expired products
     (By adding qq_it and ex_it of the selected retailer)
          If (QT1> load of fresh products & QT2> load of expired products)
          Allocate the assigned retailer of DC to route nT
          Else
          Close route nT, and Build a new route nT+1,
          Refresh the load of fresh products & load of expired products
          EndIf
     If all the assigned retailers are put in a route (DC+1)
     EndFor
If all retailers in this period are assigned to a route (t+1)
EndFor
```

Figure 6. Pseudo code to specify routes.

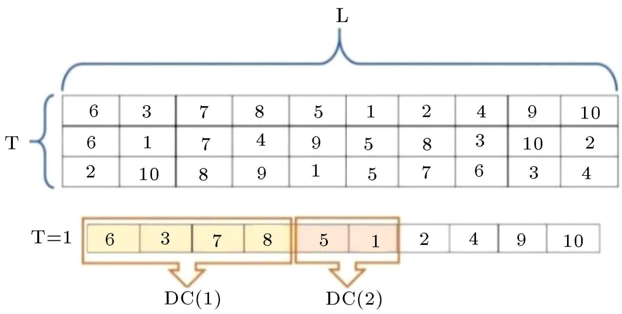

Figure 9. Process of personnel allocation.

mentioned above, the number of products that must be delivered to the retailers in each period, including the product needed for the current period and a random percentage of the products for the next periods, qq_{it} and q_{it}, should be determined. Two main limitations namely the retailer's capacity and the product's shelf life are controlled in generating qq_{it} and q_{it}. Moreover, the expired products at the end of each period (ex_{it}) can be calculated considering qq_{it}, q_{it} and the product's shelf life.

The single-point crossover and inversion mutation are used to generate offspring. These operators are described by Rabbani et al. [18] in detail. In the hybrid algorithm, the MOPSO algorithm with continuous solution space is merged. Thus, a continuous equivalent for the initial solution is required. Instead of permutation, continuous numbers with uniform distribution in [0, 1], sorted from small to large, are ranked for further use. Furthermore, the second to fourth matrices filled by integer numbers in a certain range should be adjusted. Herein, continuous numbers with uniform distribution in [0, 1] are generated, and its related integer is replaced based on which interval each number belongs.

4.6. Test problem generation

Since a new network design for a sustainable CLSC is proposed in this study, there is no benchmark or data set in the literature to use for model verification. Therefore, some medium- and large-sized test problems are generated and inspired by the studied case study. Table 7 is used to set the size of the test problems. The test problem parameters are available at http://dx.doi.org/10.17632/3d286djjfd.1.

5. Computational results and sensitivity analysis

To demonstrate the effectiveness of the developed hybrid multi-objective algorithm, it is compared with the conventional algorithm (i.e., NSGA-II) based on multi-objective comparison metrics. Firstly, the parameters of the two proposed algorithms are tuned. Then, outputs of the proposed algorithms are reported and compared using bar charts and t-test. Finally, the sensitivity analysis is done on the selling price of recycled products as an influential parameter.

Table 7. Size of test problems.

No.	**Problem size** $\lvert D\rvert \times \lvert G\rvert \times \lvert I\rvert \times \lvert R\rvert \times \lvert S\rvert \times \lvert L\rvert \times \lvert T\rvert$
0	$2 \times 2 \times 5 \times 2 \times 2 \times 10 \times 3$
1	$3 \times 2 \times 6 \times 2 \times 2 \times 20 \times 3$
2	$3 \times 2 \times 8 \times 3 \times 2 \times 25 \times 3$
3	$4 \times 2 \times 12 \times 3 \times 2 \times 30 \times 3$
4	$6 \times 2 \times 18 \times 4 \times 2 \times 40 \times 4$
5	$8 \times 3 \times 24 \times 4 \times 3 \times 60 \times 4$
6	$10 \times 3 \times 30 \times 5 \times 3 \times 80 \times 4$
7	$12 \times 3 \times 40 \times 8 \times 3 \times 100 \times 5$
8	$15 \times 3 \times 50 \times 10 \times 3 \times 140 \times 5$
9	$18 \times 4 \times 60 \times 12 \times 4 \times 180 \times 5$
10	$20 \times 4 \times 70 \times 15 \times 4 \times 200 \times 6$

5.1. Comparison metrics

To evaluate the performance of the meta-heuristics, four comparison metrics are applied:

1. Number of Pareto front Solutions (NPS): It refers to the number of non-dominated points that each algorithm obtains, which shows the high ability of each algorithm to find efficient points.
2. Computational Time (CT): It indicates the time taken by each algorithm to find the Pareto front. The low value of CT shows the better performance of an algorithm.
3. Spacing Metric (SM): It means how non-dominated solutions are distributed throughout the obtained Pareto front. The lower value of the SM shows the more uniform distribution of Pareto points. It is calculated as follows [18]:

$$SM = \sqrt{\frac{1}{NPS-1}\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2}, \tag{55}$$

$$d_i = \min_{i \neq j}^{j} \sum_{k=1}^{k} \left| f_k^i(\vec{x}) - f_k^j(\vec{x}) \right|$$

$$i, j = 1, 2, ..., NPS, \tag{56}$$

where $\bar{d}$ is the average value of d_is. $\vec{x}$ is the solution vector, k is the index of the kth objective function, and i and j are the indexes of Pareto solutions.

4. Diversity Metric (DM): It distinguishes the spread of solution sets calculated as follows:

$$DM = \sqrt{\sum_{k=1}^{K}\left(\max_i f_k - \min_i f_k\right)^2}, \tag{57}$$

where k is the index of the kth objective function, and i is the index of Pareto solutions.

5.2. Parameters tuning

The performance of meta-heuristics is highly dependent on their parameter values; therefore, the calibration of their parameters is essential. Here, the Taguchi Design of Experiment (DOE) method, as a powerful tool for parameter tuning [49], is employed for parameter setting of algorithms. One of the distinctive features of the Taguchi method is achieving the most extensive information by generating the least number of experiments [49].

A three-level Taguchi design is applied to analyze the influence of vital parameters of NSGA-II involving population size (Np), the total number of iterations (*Max Iteration*), crossover rate (Pc), and mutation rate (Pm) shown in Table 8.

Besides the aforementioned parameters, the three levels of repository size (Nr), leader selection pressure (Beta), deletion pressure (Gamma), inertia weight (w), personal learning coefficient (c_1), and global learning coefficient (c_2) are given in Table 9 for the proposed NSGA-II-MOPSO algorithm.

Based on the Taguchi method, it is enough to use L9 orthogonal array (nine experiments) for the NSGA-II [50] instead of 34 full factorial experiments and L27 orthogonal array (27 experiments) instead of 310 full factorial experiments for the hybrid NSGA-II-MOPSO algorithm. The L9 and L27 orthogonal arrays are available in MINITAB software, version 17.

Table 8. Levels of parameters for the NSGA-II.

NSGA-II parameters	Levels 1	2	3
Max iteration	80	100✓	120
Population size	50	100	150✓
Crossover probability	0.6	0.7✓	0.8
Mutation probability	0.2	0.3✓	0.4

Here, Taguchi is employed on Problem No. 1. The response variable of the Taguchi is the weighted average of the four main comparison metrics (i.e., CT, NPS, DM, and SM). To avoid the effect of scales on computations, values of metrics should be normalized as follows. If higher values of a metric (x) are desirable (e.g., NPS and DM), it is denoted by x^+ and normalized by Eq. (58). However, if lower values of a metric are desired (e.g., CT and SM), x^- is its symbol and will be normalized by Eq. (59):

$$x^+ \rightarrow r_i = \frac{x_i - \min_i(x_i)}{\max_i(x_i) - \min_i(x_i)}, \tag{58}$$

$$x^- \rightarrow r_i = \frac{\max_i(x_i) - x_i}{\max_i(x_i) - \min_i(x_i)}. \tag{59}$$

Regarding the NSGA-II, by doing nine experiments with different levels of the parameter, the values of metrics are measured and normalized in Table 10, which also reported weights. Due to the widespread metrics data for the hybrid NSGA-II-MOPSO, their values are not reported here.

Figure 10 shows the experimental results of NSGA-II and NSGA-II-MOPSO parameters tuning. In Taguchi, a robustness measure, signal-to-noise (S/N) ratio, is used to identify control factors and reduce the effects of noise factors. Higher values of the S/N ratio specify control factor settings that minimize the effects of the noise factors [51]. The desirable levels of each

Table 9. Levels of parameters for the hybrid NSGA-II-MOPSO.

NSGA-II-MOPSO parameters	Levels 1	2	3
Max iteration	80✓	100	120
Population size	50	100✓	150
Repository size	20✓	40	60
Crossover probability	0.6	0.7✓	0.8
Mutation probability	0.2	0.3✓	0.4
Beta (leader selection pressure)	0.8	1.2✓	2.4
Gamma (deletion selection pressure)	0.8	1.2	1.4✓
Weight of inertia	0.5✓	0.7	0.9
Personal learning (c_1)	1	1.25	1.5✓
Global learning (c_2)	1✓	1.5	2

Table 10. Values and normalized values of metrics for nine NSGA-II experiments.

RUN	CT(0.2)	NPS(0.2)	DM(0.3)	SM(0.3)	Response
1	105.142	50	21421.1	613.71	
	(1)	(0)	(0)	(0.326282)	0.297885
2	167.587	100	85098	377.702	
	(0.867305)	(0.5)	(1)	(0.658177)	0.770914
3	371.973	150	47398.1	431.552	
	(0.432989)	(1)	(0.40795)	(0.58245)	0.583718
4	173.621	50	76568.1	439.558	
	(0.854483)	(0)	(0.866045)	(0.57119)	0.602067
5	441.866	97	44443.6	396.191	
	(0.284467)	(0.47)	(0.361552)	(0.632177)	0.449012
6	410.854	147	76998.4	134.635	
	(0.350367)	(0.97)	(0.872801)	(1)	0.825914
7	152.874	50	48602.8	327.439	
	(0.898570)	(0)	(0.426869)	(0.728862)	0.526433
8	449.621	100	46711.6	669.836	
	(0.267988)	(0.5)	(0.397169)	(0.247354)	0.346954
9	575.734	150	59786.4	845.727	
	(0)	(1)	(0.602499)	(0)	0.38075

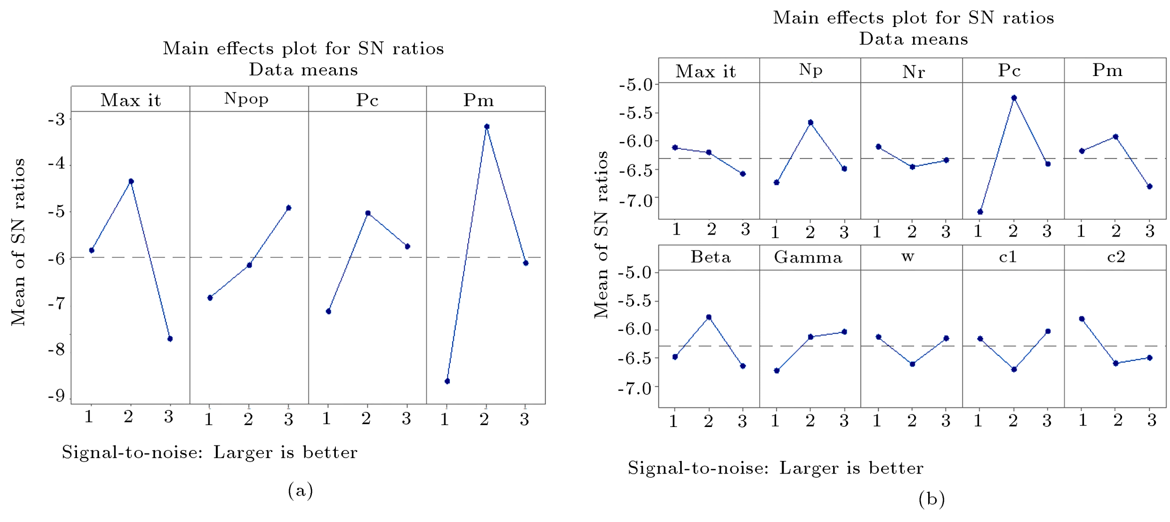

Figure 10. NSGA-II (a) and NSGA-II-MOPSO (b) parameters tuning by the Taguchi DOE.

parameter, which have the maximum mean of the S/N ratio, are marked in Tables 8 and 9.

5.3. Results of meta-heuristics

In this section, the case study described in Section 4.1 is solved by two developed meta-heuristics, and obtained results are compared with those obtained by the TH method. For this purpose, both meta-heuristics are coded in MATLAB version R2016b. The value of each objective function reported in Table 11 is the average of that objective function values for obtained Pareto solutions. As shown in Table 11, the solving time of two developed meta-heuristics is much shorter than the TH method. The results reported in this table verify the acceptable performance of developed algorithms in both speed and accuracy for small-sized problems. The medium- and large-sized problems generated in Section 4.6 are not solvable by the TH method in a reasonable time. Therefore, these problems are solved using only two developed meta-heuristics, and

Table 11. Results of solving the case study by the developed meta-heuristic algorithm.

Problem (0)	$2 \times 2 \times 5 \times 2 \times 2 \times 7 \times 3$			
Solving method	**obj 1**	**obj 2**	**obj 3**	**Computational time (s)**
Exact	10037.02	6123.415	57.9726	1440
NSGA-II	10945	6490	54.9	210.922
NSGA-II-MOPSO	10578	6753	52.6	160.56

Table 12. Objective function values of medium- and large-sized problems.

	Solving method					
	NSGA-II			NSGA-II-MOPSO		
Number	**Obj 1**	**Obj 2**	**Obj 3**	**Obj 1**	**Obj 2**	**Obj 3**
1	23482	9565.29	19	34413	9518.5	19
2	43904.5	18237.5	20.5	24034	20930	20
3	53861.5	28073.5	22.5	44598.5	28509	28
4	67791	50094.5	56.5	100870	64892.5	57.5
5	96077	75479	84	149520	77120	80
6	163575	90897	105	176315	90390	105
7	262445	153760	165	307975	16941.5	185
8	293430	179815	200	418805	206910	220
9	371120	212640	240	538555	255265	290
10	584590	312140	370	665140	345065	405
Avg.	196028	113070	128.25	246023	111554	140.95

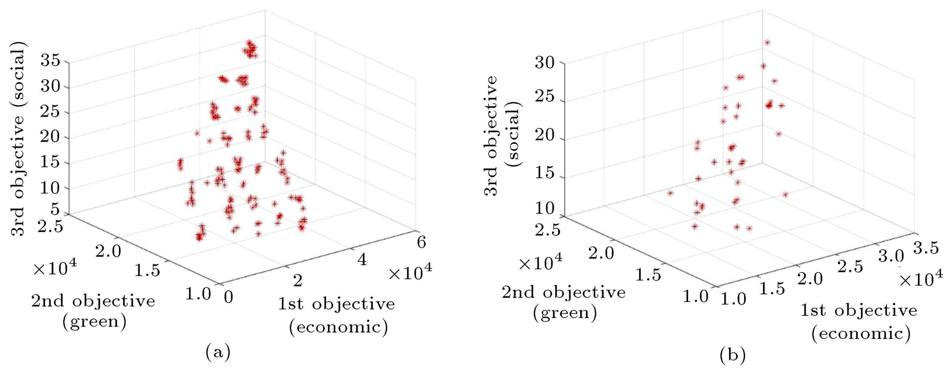

Figure 11. NSGA-II (a) and NSGA-II-MOPSO (b) Pareto front for Problem No. 1.

the average of objective functions regarding the Pareto front is reported in Table 12.

The Pareto solutions for Problem No. 1 obtained by the NSGA-II and NSGA-II-MOPSO algorithms are depicted in Figure 11. Table 13 reports the value of comparison metrics for both algorithms. The values of metrics show the acceptable performance of the developed algorithms. As shown, by increasing the problem size, the CT is also increased, but not in a non-polynomial manner. According to Figure 12, although the NSGA-II generates more Pareto solutions than the NSGA-II-MOPSO, the NSGA-II-MOPSO algorithm has shorter CT due to the application of global and personal best memory. Compared with the hybrid algorithm, the average of the CT for the NSGA-II is about 2.5 times higher.

The comparison of the NPS and the CT is visible by visual tools. However, a statistical paired t-test is applied to compare the two algorithms based on DM and SM [52]. Is there any difference in the mean of metrics? The paired t-test checks the hypothesis that DM and SM averages of the problem solved by the

Table 13. Comparison of metrics for all test problems solved by the meta-heuristic algorithms.

	Solving method							
	NSGA-II				NSGA-II+MOPSO			
Number	NPS	CT	SM	DM	NPS	CT	SM	DM
1	149.5	686.01	587.86	50283.46	43	280.94	1275.11	39215.91
2	150	564.84	450.66	66974.38	27	175.39	1831.28	31659.29
3	150	740.79	1097.46	84805.57	36	329.55	2549.86	63160.06
4	150	1289.04	1063.99	82289.67	30.5	516.20	2259.80	63363.62
5	150	1829.46	1589.44	115534.84	24	719.83	3031.04	67915.54
6	150	2413.91	2173.89	196498.64	32	919.88	3200.55	101544.32
7	148	3548.40	3766.65	270177.99	21.5	1361.19	4559.14	104738.16
8	150	5357.59	4252.88	315787.54	24.5	2111.51	5047.74	176943.67
9	150	7149.93	3660.71	380093.08	17.5	2476.42	6054.67	143434.65
10	150	9415.76	4403.10	438262.53	22	4526.44	6585.65	122197.37
Avg.	149.75	3299.57	2304.66	200070.77	27.8	1341.74	3639.48	91417.26

Table 14. Results of the paired t-test for the DM and the SM.

	Mean		STD			Confidence interval				
Metrics	NSGA-II	NSGA-II-MOPSO	NSGA-II	NSGA-II-MOPSO	Mean difference	down	up	t-value	DF	p-value
DM	200071	91417	134877	44364	108654	42156	175151	3.64	9	0.005
SM	2305	3639	1486	1728	-1330	-1702	-968	-8.10	9	0

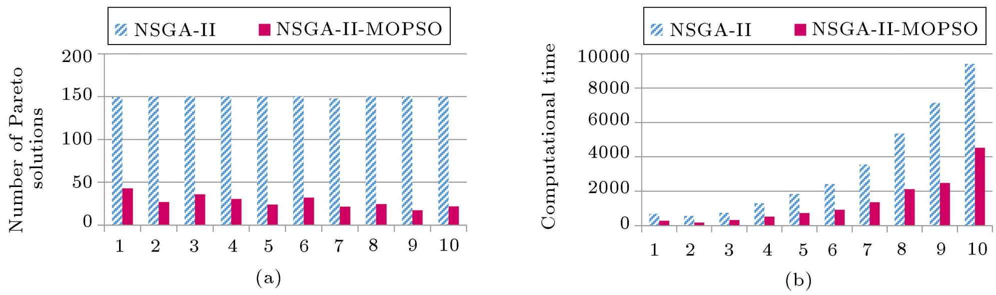

Figure 12. NPS (a) and CT (b) of the NSGA-II versus the NSGA-II-MOPSO.

hybrid algorithm remain equal to the DM and the SM averages of the problem solved by NSGA-II. Since DM and SM have a normal distribution, the paired t-test is allowed to be used. At a confidence level of 95%, if the p-value is under 0.05, the hypothesis is rejected. The outputs of running the paired t-test are reported in Table 14 to determine the best algorithm.

Regarding Table 14, the p-value is less than 0.05 for both the DM and SM metrics. Therefore, there is a meaningful difference in the performance of two algorithms. Based on the obtained statistical data, the NSGA-II has higher diversity with less spacing than the NSGA-II-MOPSO and, consequently, has better performance in terms of the DM and SM metrics. However, if the decision-maker cares about the CT, a hybrid algorithm should be selected.

5.4. Sensitivity analysis

Since the selling price of recycled products to the secondary market, P_t, is a significant parameter in the considered problem, this parameter is analyzed here. It is a prominent parameter, because if this price is deducted, perhaps the retailer will not be able to bear the holding cost of perishable inventory plus the risk of not selling it. The results of the sensitivity analysis on Pt are shown in Figure 13. According to Figure 13(a),

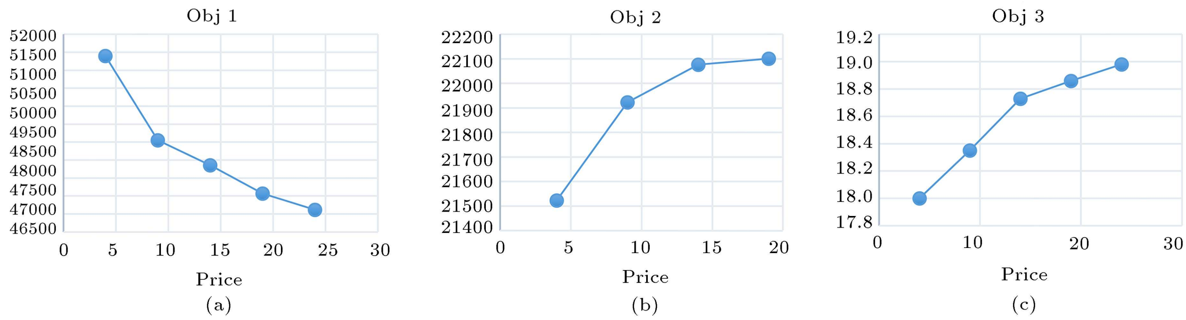

Figure 13. Economic (a), environmental (b), social (c), and effects of the selling price of recycled products.

since increasing the price of selling recycled products to the secondary market up to six times brings about greater profit, the first objective function experiences a decreasing trend (−8.33%), while it causes more RCs to operate, which in turn increases the employment rate. Herein, an increase in the social objective function is observed (+5.44%) in Figure 13(c). When the retailers know that the expired products can be sold out to the secondary market at higher prices, more products will be delivered to the retailers, resulting in increased vehicle FCR and GHG emissions (+2.85%) (Figure 13(b)). Consequently, it is imperative to decide on this price at first and, then, plan the supply chain network.

6. Conclusions and future research

This study proposed a new sustainable location-routing-inventory model, called Closed-Loop Location-Routing- Inventory Problem (CL-LRIP), to plan an efficient closed-loop supply chain for perishable products. To do this, a multi-objective mathematical programming model was proposed to minimize the total costs and environmental impacts while maximizing the utility of three main network stakeholders. Then, the chance-constrained possibilistic programming method was employed to encounter uncertainty in the parameters of the model. Afterward, the TH method was applied to convert the multi-objective model into a single one solved by CPLEX solver of GAMS software. Since the problem is NP-complete, exact methods were inefficient to solve the problem in large-sized instances. Hence, a hybrid metaheuristic algorithm was developed to solve the proposed model in large-sized instances. The obtained results showed the efficiency and performance of the proposed model and the applied NSGA-II-MOPSO algorithm. Likewise, the results pointed to the validity and applicability of the proposed model in a case study from the bread industry. The results of solving the problem indicated that the developed hybrid algorithm can obtain high-quality solutions with 89% lower CPU time than the exact method. Finally, a sensitivity analysis was conducted on important parameters of the proposed model and the obtained results demonstrated that the sale price of the recycled products had a significant impact on sustainability goals, such that increasing it by six times caused an 8.33% decrease in the economic objective, a 2.83% rise in environmental side-effects, and a 5.44% increase in social goals. Therefore, supply chain managers are required to determine the prices at the secondary market before the planning of the supply chain. Some of the future research directions are:

i) Considering the risk of roads' or facilities' disruption;

ii) Tacking into account scheduling decisions of the plant;

iii) Embedding pricing decisions of the second bazaar into the developed model. Moreover, solving the problem with a customized exact method or finding a lower bound for it can be a contribution to the solution methods.

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