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; remained perished products at retailers can be gathered for recycling during distributing fresh products. 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 causes 9.08% increase in costs, 2.77% decrease in environmental side-effects, and 5.16% decrease in social objectives, which are significant.

Keywords: Closed-loop supply chain; Location-routing-inventory problem; Perishability; Simultaneous pickup and delivery; Sustainability; Multi-objective meta-heuristics.

1. Introduction

The distribution type of product waste 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 feed 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. So, some parts of a retailer's perishable inventories can perish in each period because of losing quality, becoming out of date, etc. [5].

Sustainable Supply Chain Management (SSCM) refers to designing products and distribution networks, which causes no harm to recent or future generations considering the economic, environmental, and social consequences [6]. Thus, the satisfaction of all stakeholders in the supply chain should be taken into account. Based on 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.

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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 second market after reprocessing [5]. Govindan et al. [2] stated that low-quality products can be sold to a second market at a lower price, especially in societies, in which people in various areas have different Maximum Willingness to Pay (MWP). So, a CLSC can help the reduction of resource consumption and waste generation to achieve global sustainability [9].

This paper is among the first studies, which deals with a Closed-Loop Location-Routing-Inventory Problem (CL-LRIP) considering: simultaneous pickup and delivery for perishable products, the possibility of selling recycled products to a secondary market, the possibility of applying different technologies, each one with a specified economic, social and environmental specification at DCs and RCs and, 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 remained products (visiting each retailer twice). Using multi-compartment vehicles are inspired by Moon, Salhi, & Feng [10] utilized a multi-compartment fleet for different types of products.

This problem is inspired by some real-world observations. For instance, some of the applications of the proposed model are in fruit/vegetable distribution networks that DCs dispatch products to retailers, but the unsold remained products can be sold at a lower price to workshops, which produce dried fruits/vegetables to supply a part of their demands; in industrial bread case, one of the resources for supplying bread demands that people usually avoid buying low-quality/stale bread, remained bread can be collected and turned into a toasted flour for humans or animals and poultry feed; in some similar cases in the dairy industry; in the fashion industry; and in cut flower supply chains that unsold flowers 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 (DC), retailers/customers, Recycling Centers (RCs), and a Central Disposal Center (CDC). The proposed model aims to find the following answers: 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 to the second product, the impacts of the leading stockholder’s utility functions on optimal location, routing, and inventory decisions, and 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 tries to minimize costs while 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 impact 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 conserved by their utility functions.

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

2. Literature Review

By reviewing 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 just focus on economic and environmental issues, maybe because of international targets, such as a 500 million tons reduction in GHG emissions between 2015 and 2035 by the European Commission [12]. However, sustainability’s social aspects are a matter of great concern, especially in labor-intensive industries. In Table 1, some social criteria studied in quantitative models are summarized.

Integrating forward and reverse logistics that cause the formation of a CLSC [13], strongly influence 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 back-haul, the amounts of wastes/environmental side-effects as well as costs are reduced [14]. In designing forward and reverse logistics, just 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 on CLSC is presented by Govindan et al. [8].

(Table 1 Near Here)

Since based on sustainable development pillars, inventory management of the deteriorating products, divided to perishable and decaying products due to Bakker et al. [21], can cause environmental protection, job creation, and financial benefits [22], this study focuses on perishable products. It becomes more challenging when the transportation and vehicle routing of perishable products should be managed because of the influence on the environment [23]. A systematic review has been done on inventory models of perishable products by Chaudhary et al. [24]. Different approaches for modeling perishability of products have been found, including 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 a 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 passing holding time from the shelf life of product causes spoilage. They added the concept of reverse logistics to the IRP to increase the sustainability of the perishable products distribution network. Also, Rahimi et al. [31] formulated a fuzzy multi-objective IRP model considering maximizing profit, maximizing service level, and minimizing the GHG emissions of network activities.

In this paper, a Location-Routing-Inventory Problem (LRIP) was introduced by Ahmadi Javid and Azad [32] by integrating the LRP, which is reviewed by Prodhon and Prins [33] and 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 objectives 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 minimizes 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 to solve an integrated location-inventory-routing problem for the supply chain design by Zheng et al. [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 taken 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). The 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 illustrated.

According to Table 2, a limited number of researches on the LRIP concentrates on perishable products. For instance, Hiassat et al. [39] by considering a limited deterministic shelf life for products, 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, which should be delivered in a limited time horizon. However, some real assumptions are not studied in previous models, such as gathering perished products via a VRP with simultaneous pickup and delivery; using multi-compartment trucks for forward and backward flows; collecting the expired products, turning them to the second product in recycling centers, and selling them in a secondary market; considering all pillars of sustainable development; 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) has to supply the uncertain demands of retailers through several DCs. Products first should be received by DCs and after that 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). Also, 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 occur in the soft time windows of the DCs. Otherwise, it causes a penalty cost. A soft time window is also included for retailers/customers. Unlike DCs, the violation of the retailer’s time windows influences 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 tried to improve network performance by sharing the transportation fleet in the forward and reverse flows. Each compartment of the truck has limited capacity. The cold compartment for transporting fresh products consumes energy to provide the 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 also should find the 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 to reach their home sooner and increase their work satisfaction.

Usable perished products are reprocessed and turned into new products for the second market in operated RCs. The value-added products can be sold to a second 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 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 CO2 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
with 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.

### 3.1. 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.

### 3.2. Notations

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<td>$dp_{ld}$</td>
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\( \tilde{a}_l \) 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 \( n' \)

\( t_{mn} \) Time of traveling from node \( m \) to node \( n \)

\( \varphi_{mnt} \) Urban traffic risk between node \( m \) and \( n \) in period \( t \)

\( F_Y \) Fixed cost of hiring a multi-compartment truck

\( Q_{1t} \) Capacity of the first part of 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 multi-compartment truck (without freezer)

\( C_{t'm'n'n'} \) 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 \( i \)

\( tw_{it} \) Desired time window of retailer \( i \) in period \( t \) states by a trapezoidal fuzzy number, \( tw_{it} = (tw_{1it}, tw_{2it}, tw_{3it}, tw_{4it}) \)

\( h_{it} \) Inventory holding cost of retailer \( i \) in period \( t \)

\( cap_i \) Depot capacity of retailer \( i \)

\( \theta \) Percent of perished product 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

\( Q_f \) 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 (\( wf^1 = wf^0 + Q_f \))

\( rd_d (rd_r) \) Regional development percentage of 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 the homogeneous fleet from RC \( r \) to the CDC in period \( t \)

\( Ve_{edt} \) 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 \( t \)

\( Vd_t \) Amount of product 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

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

$\gamma_{rt}^{s}$  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

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

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

$y_{ndt}$  Auxiliary variable, 1 if $NL_{dt} > 0$; 0, otherwise (i.e., $NL_{dt} = 0$)

$y_{frt}$  Auxiliary variable, 1 if $NF_{rt} > 0$; 0, otherwise (i.e., $NF_{rt} = 0$)

$u_{m}^{t}$  Deliverable load of a multi-compartment truck before starting to serve node $m$ in period $t$

$uu_{m}^{t}$  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 a received product by retailer $i$ in period $t$

$q_{il}^{tt}$  Quantity of received product 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 $d$, $up_{ld}$, defined as follows:

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

Equation (1)

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

$$
uc_{it} = \begin{cases} 
0 & at_{it} < tw_{1it} \text{ or } at_{it} > tw_{4it} \\
\frac{at_{it} - tw_{1it}}{tw_{2it} - tw_{1it}} & tw_{1it} \leq at_{it} < tw_{2it} \\
1 & tw_{2it} \leq at_{it} \leq tw_{3it} \\
\frac{tw_{4it} - at_{it}}{tw_{4it} - tw_{3it}} & tw_{3it} < at_{it} \leq tw_{4it} 
\end{cases}
$$

Equation (2)

3.3. Mathematical Formulation
Objective functions:

\[
\text{Min } f_1 = \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} Nl_{dt} Cl_{dt} Dp_d + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} f d_{dgt} y_{dgt} + \sum_{t=1}^{T} \sum_{d=1}^{D} (p e_{vt} e_{dt} + p l_{vt} v_{dt})
\]

\[
\sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} f v_{dgt} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} C t_{mn} b_{mtn} x_{mtn} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} C t_{mtr} b_{rtr} y_{rtr} +
\]

\[
\sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} f r_{rtr} x_{rtr}^2 + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} N f_r C f_r b_d + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} f d_{dgt} y_{dgt} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} f d_{dgt} y_{dgt}^2 + (10 - \theta) uu_d \]

\[
\text{Min } f_2 = \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} c e_{dg} y_{dgt}^2 + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} c e_{rtr} y_{rtr} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} (1 + ce_{dgt}) Dp_d F C R t_{dgt} (N t_{dt} - 1) y_{dgt}
\]

\[
+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} (1 + ce_{dgt}) Dp_d F C R t_{dgt} (N t_{dt} - 1) y_{dgt}
\]

\[
+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} (1 + ce_{dgt}) Dp_d F C R t_{dgt} (N t_{dt} - 1) y_{dgt}
\]

\[
+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} (1 + ce_{dgt}) Dp_d F C R t_{dgt} (N t_{dt} - 1) y_{dgt}
\]

\[
+ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} (1 + ce_{dgt}) Dp_d F C R t_{dgt} (N t_{dt} - 1) y_{dgt}
\]

\[
\text{Max } f_3 = \alpha_1 \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} p r_{dgt} u_{dgt} + \alpha_2 \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} w_{dgt} u_{dgt} + \alpha_3 \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} \left( \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} y_{dgt} f_{dgt} (1 - r d_g) \right)
\]

\[
\sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} y_{dgt} f_{dgt} (1 - r d_g) + \left\{ \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} y_{dgt} r_p_{dgt} + \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{g=1}^{G} y_{dgt} r_p_{dgt} \right\}
\]

Constraints:

\[
N l_{dt} \geq V_{dt} / Q I \quad \forall t \in T, \forall d \in D
\]

(6.1)

\[
N l_{dt} \leq V_{dt} / Q I + 1 \quad \forall t \in T, \forall d \in D
\]

(6.2)

\[
V_{dt} \leq Q_d \sum_{g=1}^{G} y_{dgt} \quad \forall t \in T, \forall d \in D
\]

(7)

\[
\sum_{g=1}^{G} y_{dgt} \leq 1 \quad \forall t \in T, \forall d \in D
\]

(8)

\[
V_{dt} = \sum_{t=1}^{T} y_{dgt} q q_{dgt} z_{dgt} \quad \forall t \in T, \forall d \in D
\]

(9)

\[
\sum_{d=1}^{D} z_{dgt} = 1 \quad \forall t \in T, \forall i \in I
\]

(10)

\[
\sum_{t=1}^{T} z_{dgt} \leq M \sum_{g=1}^{G} y_{dgt} \quad \forall t \in T, \forall d \in D
\]

(11.1)
\[
\sum_{g=1}^{G} y_{d}^g \leq \sum_{i=1}^{l} z_{id} \quad \forall t \in T, \forall d \in D
\]  
(11.2)

\[
V_{e,dt} \geq (e_{dt} - \eta_{dt}) \sum_{g=1}^{G} y_{d}^g \quad \forall t \in T, \forall d \in D
\]  
(12.1)

\[
V_{l,dt} \geq (\eta_{dt} - l_{dt}) \sum_{g=1}^{G} y_{d}^g \quad \forall t \in T, \forall d \in D
\]  
(12.2)

\[
w_{idt} \leq \sum_{g=1}^{G} y_{d}^g \quad \forall t \in T, \forall d \in D, \forall l \in L
\]  
(13)

\[
\sum_{i=1}^{l} w_{idt} = \sum_{g=1}^{G} r_{dg} y_{d}^g \quad \forall t \in T, \forall d \in D
\]  
(14)

\[
\sum_{m=1}^{M} x'_{im} = 1 \quad \forall t \in T, \forall i \in I, i \neq m
\]  
(15)

\[
\sum_{n=1}^{M} x'_{im} = \sum_{n=1}^{M} x'_{mn} \quad \forall t \in T, \forall m \in M
\]  
(16)

\[
\sum_{d=1}^{D} x'_{id} \mu \nu_i \leq M \sum_{j=1}^{P} \gamma x_{ij} \quad \forall t \in T, \forall i \in I
\]  
(17.1)

\[
\sum_{r=1}^{g} y x_{ir} \leq M \sum_{d=1}^{D} x'_{id} \mu \nu_i \quad \forall t \in T, \forall i \in I
\]  
(17.2)

\[
\sum_{r=1}^{g} y x_{ir} \leq 1 \quad \forall t \in T, \forall i \in I
\]  
(17.3)

\[
\sum_{r=1}^{g} y x_{ir} \leq M \sum_{s=1}^{l} \gamma x_{is} \quad \forall t \in T, \forall r \in R
\]  
(18.1)

\[
\sum_{s=1}^{g} y x_{sr} \leq \sum_{i=1}^{l} \gamma x_{is} \quad \forall t \in T, \forall r \in R
\]  
(18.2)

\[
\sum_{s=1}^{g} y x_{sr} \leq 1 \quad \forall t \in T, \forall r \in R
\]  
(19)

\[
x_{id} \leq z_{id} \quad \forall t \in T, \forall i \in I, \forall d \in D
\]  
(20)

\[
x_{id} \leq z_{id} \quad \forall t \in T, \forall i \in I, \forall d \in D
\]  
(21)

\[
x_{ij} + z_{id} + \sum_{d=1}^{D} z_{id} \leq 2 \quad \forall t \in T, \forall i, j \in I, i \neq j, \forall d \in D
\]  
(22)

\[
\sum_{r=1}^{l} \mu \nu_i x'_{ir} \leq Q \sum_{r=1}^{s} \gamma x_{ir} \quad \forall t \in T, \forall r \in R
\]  
(23)

\[
u_{j} - u_{j} + x'_{j} Q_{lt} + (Q_{lt} - q_{lt} - q_{lt}) x_{j} \leq Q_{lt} - q_{lt} \quad \forall t \in T, \forall i, j \in I, i \neq j
\]  
(24)

\[
u_{ij} - u_{ij} + x'_{j} Q_{2lt} + (Q_{2lt} - e_{lt} - e_{lt}) x_{ij} \leq Q_{2lt} - e_{lt} \quad \forall t \in T, \forall i, j \in I, i \neq j
\]  
(25)

\[
u_{i} \leq Q_{lt} - (Q_{lt} - q_{lt}) \sum_{d=1}^{P} x_{id} \quad \forall t \in T, \forall i \in I
\]  
(26)

\[
u_{ij} \leq Q_{2lt} - (Q_{2lt} - e_{lt}) \sum_{d=1}^{P} x_{ij} \quad \forall t \in T, \forall i \in I
\]  
(27)
\[ u^t_d = \sum_{i=1}^I z_{id} q_{ji} u^t_i \quad \forall t \in T, \forall d \in D \] (28)

\[ uu^t_d = \sum_{i=1}^I z_{id} \mathbf{e} \quad \forall t \in T, \forall d \in D \] (29)

\[ qa_i + \sum_{j=1}^J x_{ji} q_{ji} \leq u^t_i \quad \forall t \in T, \forall i \in I \] (30)

\[ ex_a + \sum_{j=1}^J x_{ji} \mathbf{e} \leq uu^t_i \quad \forall t \in T, \forall i \in I \] (31)

\[ at_i + M (1 - x^t_i) \geq t_t a_i (1 + \varphi^{at}) \quad \forall t \in T, \forall i \in I, \forall d \in D \] (32.1)

\[ at_i - M (1 - x^t_i) \leq t_t a_i (1 + \varphi^{at}) \quad \forall t \in T, \forall i \in I, \forall d \in D \] (32.2)

\[ at_j + M (1 - x^t_j) \geq at_i + t_t_a (1 + \varphi^{at}) \quad \forall t \in T, \forall i \in I, \forall j \in I \] (33.1)

\[ at_j - M (1 - x^t_j) \leq at_i + t_t_a (1 + \varphi^{at}) \quad \forall t \in T, \forall i \in I, \forall j \in I \] (33.2)

\[ Nf_{fr} \geq \theta \sum_{i=1}^I uu^t_i, yc_{fr}, /Qf \quad \forall t \in T, \forall r \in R \] (34.1)

\[ Nf_{fr} \leq \theta \sum_{i=1}^I uu^t_i, yc_{fr}, /Qf + 1 \quad \forall t \in T, \forall r \in R \] (34.2)

\[ I_i = I_{i-1} + qa_i - d_i - ex_i \quad \forall t \in T, \forall i \in I \] (35)

\[ qa_i \leq cap, - I_{i-1} \quad \forall t \in T, \forall i \in I \] (36.1)

\[ I_i \leq cap_i \quad \forall t \in T, \forall i \in I \] (36.2)

\[ q_{im} \leq cap_i \quad \forall t \in T, \forall i \in I \] (36.3)

\[ Ex_i = \sum_{k=1}^T q_{i(t-s)k} \quad \forall t \in T, \forall i \in I, t \geq SL \] (37.1)

\[ Ex_i = 0 \quad \forall t \in T, \forall i \in I \] (37.2)

\[ \sum_{i=1}^T q_{im} = qa_i \quad \forall t \in T, \forall i \in I \] (38)

\[ \sum_{i=1}^T q_{im} = 0 \quad \forall t \in T, \forall i \in I \] (39)

\[ Nl_{di} \leq M y_{di} \quad \forall t \in T, \forall d \in D \] (40)

\[ Nf \leq M y_{fr} \quad \forall t \in T, \forall r \in R \] (41)

\[ y^x_{di}, y^y_{di}, w_{di}, z_{di}, x_{mo}, x_{ma}, y_{iy}, y_{if}, y_{fr}, y_{fr}, \{0,1\} \]

\[ Nl_{di}, Nf \in Z^+ \quad \text{On their domain} \] (42)

\[ V_{de}, v_{de}, v_{de}, a_{de}, u^t_i, uu^t_i, I_i, q_{im}, q_{im}, \text{Ex}_i \geq 0 \]

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 DCs time windows, hiring 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 respectively, minus the revenue of new products sold to the second market.
The second objective function minimizes the environmental side-effects, including CO\textsubscript{2} emission of activating/operating DCs /RCs, FCR, and CO\textsubscript{2} emission of lorries, multi-compartment trucks, and homogeneous fleet, respectively. The FCR and CO\textsubscript{2} emission of vehicles are formulated based on the traveled distance and weight of the carried loads. Xiao et al. [43] have plotted real data and calculated the FCR of fully-loaded and unloaded trucks per kilometer. In Equation (4), the FCR of partially-loaded multi-compartment trucks is computed with a linear interpolation by considering the summation of two variables, deliverable load \((u_m^f)\) and picked up load \((uu_m^f)\).

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 (Equation (1)). The social objective function also 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 DCs capacity level at each period. Constraint (8) ensures that a DC can work with just one technology level. Constraint (9) calculates the demands assigned to an active DC. Constraint (10) vouches that each retailer should be assigned to just 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's 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 the 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 constraint (16). Constraints (17.1) to (17.3) assign operated RCs to the last retailer of routes if any expired products were loaded on the multi-compartment truck. If no expired product was picked 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 can be activated with just one technology level. Constraints (20) - (22) prevent the creation of unauthorized routes. There are the structural constraints of the Location Routing Problem with Simultaneous Pickup and Delivery (LRPSPD). 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 can be the first retailer in a route starting from DC \(d\) (Constraint 21); or can be connected to other retailers which are allocated to the same DC (Constraint 22). Constraint (23) ensures the capacity limitation of RCs. Constraints (24) and (25) state the delivery and pick-up flows inequalities 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 is 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 on auxiliary variables \(u^f_i\) and \(uu^f_i\).

Constraints (32.1) and (32.2) calculate the arrival time at the first retailer of 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 level of the current and
previous period, the demand, received, 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 amount of expired product 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 \( y_n^d t \) and \( y_f^r t \) based on their definition. Finally, Constraint (42) determines the variable’s domain.

3.3.1. Linearization of Multiplying a Binary Variable to a Continuous Variable

This multiplicative statements has appeared in the objective functions (e.g., \( N_l dt \), \( y_n dt \) and \( N_f rt \cdot y_f rt \) in Equation (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 \( Q \) multiplies in 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:

\[
\begin{align*}
0 & \leq y \leq Mx & \text{(43.1)} \\
y & \leq Mx & \text{(43.2)} \\
y & \geq Q - M (1 - x) & \text{(43.3)} \\
Q & \geq 0, x \in \{0,1\}, y \geq 0
\end{align*}
\]

3.3.2. Linearization of Multiple Breakpoint Functions

Regarding fuzzy desired time window of retailer \( i \) in period \( t \), \( tw_{it} \), the utility function of retailer \( i \) in period \( t \), \( u_{cit} \), can be stated as a piecewise linear function of arrival time, \( at_{it} \), as follows:

\[
uc_{it} = \begin{cases} 
0 & \text{if } at_{it} < tw_{1i} \text{ or } at_{it} > tw_{4i} \\
\frac{at_{it}}{tw_{2i} - tw_{1i}} - \frac{tw_{1i}}{tw_{2i} - tw_{1i}} & \text{if } tw_{1i} \leq at_{it} < tw_{2i} \\
1 & \text{if } tw_{2i} \leq at_{it} \leq tw_{3i} \\
\frac{tw_{4i}}{tw_{4i} - tw_{3i}} - \frac{at_{it}}{tw_{4i} - tw_{3i}} & \text{if } tw_{3i} < at_{it} \leq tw_{4i}
\end{cases} \tag{44}
\]

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 to the following single function:

\[
uc_{it} = att_{it} = \frac{1}{tw_{2i} - tw_{1i}} - \frac{bb_2}{tw_{2i} - tw_{1i}} tw_{1i} + bb_3 \times 1 - att_{4it} \frac{1}{tw_{4i} - tw_{3i}} + bb_4 \frac{tw_{4i}}{tw_{4i} - tw_{3i}} \tag{45}
\]

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

\[
\begin{align*}
-Mbb_1 & \leq att_{1it} \leq tw_{1i} \cdot bb_1 & \forall t \in T, \forall i \in I \\
tw_{1i} \cdot bb_2 & \leq att_{2it} \leq tw_{2i} \cdot bb_2 & \forall t \in T, \forall i \in I \\
tw_{2i} \cdot bb_3 & \leq att_{3it} \leq tw_{3i} \cdot bb_3 & \forall t \in T, \forall i \in I \\
tw_{3i} \cdot bb_4 & \leq att_{4it} \leq tw_{4i} \cdot bb_4 & \forall t \in T, \forall i \in I \\
tw_{4i} \cdot bb_5 & \leq att_{5it} \leq Mbb_5 & \forall t \in T, \forall i \in I \\
\sum_{bp=1}^{BP} att_{bp, it} &= att_{it} & \forall t \in T, \forall i \in I, \forall d \in D \tag{46.6}
\end{align*}
\]
\[
\sum_{bp=1}^{BP} bb_{bp} = 1
\]  
(46.7)

\[bb_{bp} \in \{0,1\}, \text{att}_{bp} \geq 0\quad \forall t \in T, \forall i \in I, \forall bp \in BP\]

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

### 3.4. Dealing with Fuzzy Uncertainty

Because of the competitive market, demand is vague and uncertain. Since in many cases no distributional data is available, demand is stated by a trapezoidal fuzzy number i.e. \( \tilde{d}_{it} = (d_{it(1)} \cdot d_{it(2)} \cdot d_{it(3)} \cdot d_{it(4)}) \). 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 \( \text{Nec} \) is applied \[45\]. Constraint (35) is replaced with two below inequality:

\[\text{Nec}\{I_a \leq I_{a-1} + qq_{a} - d_{it} - ex_{a}\} \geq \beta \quad \forall t \in T, \forall i \in I \]  
(47.1)

\[\text{Nec}\{I_a \geq I_{a-1} + qq_{a} - d_{it} - ex_{a}\} \geq \beta \quad \forall t \in T, \forall i \in I \]  
(47.2)

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

\[I_a \leq I_{a-1} + qq_{a} - ((1 - \beta)d_{i_{it(1)}}, + \beta d_{i_{it(4)}}) - ex_{a}\quad \forall t \in T, \forall i \in I \]  
(48.1)

\[I_a \geq I_{a-1} + qq_{a} - ((1 - \beta)d_{i_{it(1)}}, + \beta d_{i_{it(4)}}) - ex_{a}\quad \forall t \in T, \forall i \in I \]  
(48.2)

In the rest of this study, \( \beta \) 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 out the LRIP, which is a simple form of the model presented in Section 3, belongs 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 closed-loop supply chain, which can be a sub-problem of our model without perishability and some decision levels, and acknowledged NP-completeness of the studied problem. So, 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 i.e. 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 a powerful software in solving MILP problems. For model validation, it is implemented for a real-case study. There is a plant of industrial bread in a neighboring city of Tehran. There are two DC’s 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 their applied technology to be solar or electricity. The planning horizon is three periods. So, 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 Tables 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 amount of expired products is delivered to the RCs. Also, a limited number of DCs and RCs are opened with a cheap technology level even though this technology level has high environmental side effects. Also, activating a few DCs/RCs prevents job creation through opening DCs/RCs. So, 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, 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 in solving MOPs, which gives efficient balanced and unbalanced solutions is the TH method [46]. This method is a fuzzy-based method to deal 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:

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

While the satisfaction degree for maximization objective functions formulated as Equation (50):

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

In the developed model, three objective functions are aimed. The values of the PIS are reported by solving three single objective problems in the pay-off Table 4, while the values of the NIS are specified as approximately 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:

$$\text{Max } \varphi \beta_0 + (1 - \varphi) \sum_k \theta_k \mu_k(x)$$  \hspace{1cm} (51)

$$\mu_k(x) \geq \beta_0 \quad \forall k, x \in F_k$$  \hspace{1cm} (52)

where $\beta_0 \in [0, 1]$ and $\beta_0 = \{\mu_k(x)\}$. $\varphi$ is the coefficient of compensation, which controls the minimum satisfaction level of the objectives ($\beta_0$) besides the compromise degree among the objectives. Moreover, $\theta_k$ shows the relative importance of the $k$-th objective function determined by the decision-maker based on the preferences, in a way 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.

The Pareto solutions are obtained by different values of $\varphi$, including 0.55, 0.65, 0.75, 0.85, 0.95, presented in Table 6. As the last column of this table shows, the computation time of the exact method for even a small problem is very long, let alone the medium/large-sized ones. Even the time of estimating $f^{NIS}_i$, 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 (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 method. 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**

**First step** Generating the initial population.

**Second step** Calculating fitness (objective) functions for each solution.

**Third step** 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 neighbor 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**

**First step** Employing the crossover operator with crossover rate, $P_c$, and the mutation operator with mutation rate, $P_m$; next population, $Q$, called offspring population with size $N$ is generated.

**Second step** The combination of the offspring and parents organizes the union population $R$.

**Third step** Calculating the fitness value of the union population $R$.

**Fourth step** Non-dominated sorting is applied concerning domination and crowding distance criteria, in order. The first $N$ solutions from the sorted union population $R$ is selected as the best solution to form the next iteration’s population $P_{r+1}$.

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. So, a new hybrid algorithm is developed by combining the NSGA-II and Multi-Objective Particle Swarm Optimization (MOPSO), which has memory and self-learning ability [48].

The Particle Swarm Optimization (PSO) algorithm for single-objective problems 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 \(i\)-th dimension at iteration \(t\), \(v_{pi}(t)\), is calculated by:
\[
v_{pi}(t) = wv_{pi}(t-1) + c_1 r_1 (x_{pbest}(t) - x_{pi}(t)) + c_2 r_2 (x_{gbest}(t) - x_{pi}(t))
\]  
(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)’s 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 \(i\)-th dimension at iteration \(t\), \(x_{pi}(t)\), is calculated by:
\[
x_{pi}(t) = x_{pi}(t-1) + v_{pi}(t)
\]
(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 to run, and then the 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 resulted 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 Equations (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 is attempted 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 allocated 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 assigned retailers to them is visible in two steps of Figure 4.

The allocated capacity to each active DC should be controlled periodically, which is equal to the total demand of allocated retailers to that DC. The number of trucks needed to deliver the products from the plant to DCs \((N_{lt})\) is derived from the division of assigned capacity into the truck capacity and rounding up the quotient. It is possible to calculate the violation penalty of the soft time windows \((V_{e_{dt}}, V_{l_{dt}})\) 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) randomly is produced, as demonstrated in Figure 5. So, the binary variables \(y_{dt}^g\) can be specified.

Now, by considering the demand of assigned retailers to a DC as well as the capacity of the refrigerated and normal part of the multi-compartment truck, the routes started from each DC can be determined by using the pseudo-code presented in Figure 6.

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

The third representation code: If at the end of an open route, a truck carries expired products, 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 at 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 array randomly. Whenever the last retailer in a route and the RC assigned to it are specified, the binary variables \(y_{ir}^t\) 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 \(s_{yt}^r\) can be specified.

Since the number of expired products shipped to each RC is determined. By dividing \(\theta\%\) of it by the fleet capacity, the number of required fleets, \(N_{f_{rt}}\), is obtained to transfer unusable products from an operated RC to the CDC.

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 the 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 \(w_{ltt}\) can be determined.

Random numbers are applied to determine inventory decision variables. Before generating the matrices 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 percent of the product for the next periods, \(q_{it}\) and \(q_{it}\) should be determined. Two main limitations: the retailer’s capacity and
the product’s shelf life, are controlled in generating \( q_{lt} \) and \( q_{lt} \). Also, the expired products at the end of each period (\( ex_{lt} \)) can be calculated considering \( q_{lt}, q_{lt} \) 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. So, a continuous equivalent for the initial solution is required. Instead of permutation, the rank of continuous numbers with uniform distribution on \([0,1]\), sorted from small to large, is used. Also, the second to fourth matrices, which are filled by integer numbers in a certain range, should be adjusted. Herein, continuous numbers with uniform distribution on \([0,1]\) are generated, and based on which interval each number belongs; its related integer is replaced.

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, 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/10.17632/3d286djfffd.1.

Table 7. Near Here

5. Computational Results and Sensitivity Analysis

To show the effectiveness of the developed hybrid multi-objective algorithm, it is compared by 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 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.

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 refers to the time that each algorithm spends 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 by [18]:

\[
SM = \sqrt{\frac{1}{NPS - 1} \sum_{i=1}^{n} (d_i - \bar{d})^2} \tag{55}
\]

\[
d_i = \min_{j \neq i} \sum_{k=1}^{K} \left| f_k^i(\bar{x}) - f_k^j(\bar{x}) \right|, \quad i, j = 1, 2, ..., NPS \tag{56}
\]

where \( \bar{d} \) is the average value of \( d_i \) s. \( \bar{x} \) is the solution vector, \( k \) is the index of the \( k \)-th objective function, and \( i, j \) are the indexes of Pareto solutions.

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

\[
DM = \sqrt{\sum_{k=1}^{K} (\max_i f_k - \min_i f_k)^2} \tag{57}
\]

where \( k \) is the index of \( k \)-th 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, so 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 ($N_p$), the total number of iterations ($Max \text{ Iteration}$), crossover rate ($P_c$) as well as mutation rate ($P_m$) in Table 8.

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

Based on the Taguchi method, it is enough to use $L_9$ orthogonal array (nine experiments) for the NSGA-II [50] instead of 34 full factorial experiments, and $L_{27}$ orthogonal array (27 experiments) instead of 310 full factorial experiments for the hybrid NSGA-II-MOPSO algorithm. The $L_9$ and $L_{27}$ orthogonal arrays are available in MINITAB software version 17.

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 in 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 shown as $x^+$, and normalized by Equation (58). However, if lower values of a metric are desired (e.g., $CT$ and $SM$), $x^-$ is its symbol and will be normalized by Equation (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.

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 Table 11 shows, 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. So, these problems are solved only with two developed meta-heuristics, and the average of objective functions regarding the Pareto front are 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 amounts of metrics show the acceptable performance of the developed algorithms. As shown by increasing the problem size, the computational time 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 fewer CT due to applying 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 two algorithms based on DM and SM [52]. Is there any difference between the mean of metrics? The paired t-test checks the hypothesis that DM and SM averages of the problem solved by the hybrid algorithm remain equal with 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. When the confidence level is 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.

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 becomes 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 \( P_t \) are shown in Figure 13. According to this figure, since increasing the price of selling recycled products to the secondary market up to six times, causes to gain more profit; the first objective function has a decreasing trend (-8.33%) (a). While it causes to operate more RCs, the employment rate would rise; Herein, an increase in the social objective function is observed (+5.44%) (c). When the retailers know that the expired products can be sold out to the secondary market at a higher price, more products would be delivered to the retailers that result in increased vehicle FCR and GHG emissions (+2.85%) (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 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 to a single one solved by CPLEX solver of GAMS software. Since the problem is NP-complete, exact methods are 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 showed the validity and applicability of the proposed model in a case study from the bread industry. The results of solving the problem showed 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 showed that the sale price of the recycled products has a significant impact on sustainability goals. In a way that increasing it to 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. So, supply chain managers are required to determine the price of 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, and iii) embedding pricing decisions of the second bazaar in the developed model. Also, 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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References


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Figure 1. Schematic of the CL-LRIP

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

Generate the initial population of size $N$

Objective functions evaluation for each individual

Non-dominated sorting based on ranking & crowding distance

Put personal best position of each particle equal to its current position & put velocity of each particle is equal to zero & find the global best position

Store non-dominated solutions in the repository set

Initialization phase

Generate Offspring population of size $N$ by crossover & mutation

Update velocity of each new generated particle by equation (53)

Combine parents and offspring populations

Objective function evaluation for each individual of offspring population

Select population with size of $N$ based on ranking & crowding distance

Update personal best position of each particle

Update global best position by using $Betta$

Update non-dominated solutions in the repository using $Gamma$

Use MOPSO equations (53) & (54) to update the velocity & position of population

Objective function evaluation for population

Main body

Max iteration has been reached?

Update Pareto front

Eliminate dominated solutions & add non-dominated solutions to the repository using $Gamma$

Select personal best position of each particle

Select global best position by using $Betta$

Return Pareto front

Stop

Figure 3. Proposed hybrid NSGA-II-MOPSO algorithm

Figure 4. First matrix to present a solution

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

29
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 \( q_{0t} \) and \( ex_{0t} \) 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 \( i+1 \)
EndFor

Figure 6. Pseudo code to specify routes

\[
\begin{align*}
 nT \\
T \\
1 & 1 & 2 \\
2 & 1 & 2 \\
2 & 1 & 1 & 1 \\
\end{align*}
\]

Figure 7. Third representation code to connect eligible routes to RCs

\[
R
\]

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

\[
\begin{align*}
 T \\
T=1 \\
6 & 3 & 7 & 8 & 5 & 1 & 2 & 4 & 9 & 10 \\
6 & 1 & 7 & 4 & 9 & 5 & 8 & 3 & 10 & 2 \\
2 & 10 & 8 & 9 & 1 & 5 & 7 & 6 & 3 & 4 \\
\end{align*}
\]

Figure 9. Process of personnel allocation
Figure 10. NSGA-II (a), NSGA-II-MOPSO (b) parameters tuning by the Taguchi DOE

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

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<tr>
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<th>Economic</th>
<th>Environmental</th>
<th>Social</th>
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<tr>
<td>Devika et al. [5]</td>
<td>CLSC network design</td>
<td>Total cost</td>
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<tr>
<td></td>
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<tr>
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<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td><strong>This study</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.** Significant features of the current study versus other related articles
Table 3. Optimal solution of the case study by considering just one objective function

<table>
<thead>
<tr>
<th>Period</th>
<th>Plant</th>
<th>NL</th>
<th>DC</th>
<th>Order of retailers in a route</th>
<th>RC</th>
<th>Nf</th>
<th>CDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1\textsuperscript{\checkmark} {g=2}</td>
<td>1\textsuperscript{\checkmark}5341</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2 {g=2}</td>
<td>1\textsuperscript{\checkmark}761</td>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1\textsuperscript{\checkmark} {g=2}</td>
<td>1\textsuperscript{\checkmark}4371</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2 {g=2}</td>
<td>1\textsuperscript{\checkmark}561</td>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1\textsuperscript{\checkmark} {g=2}</td>
<td>1\textsuperscript{\checkmark}437(RC:1)</td>
<td>1\textsuperscript{\checkmark} {s=2}</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2 {g=2}</td>
<td>1\textsuperscript{\checkmark}56(RC:1)</td>
<td>1</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4. Pay-off table

<table>
<thead>
<tr>
<th>$x_i^*$</th>
<th>Desired orientation of $f_i$</th>
<th>$f_1$</th>
<th>$f_2$</th>
<th>$f_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1^*$</td>
<td>$\text{Min } f_1$</td>
<td>$f^{PI}_{1} = 7254.767$</td>
<td>$f_2(x_1^*) = 6449.520$</td>
<td>$f_3(x_1^*) = 30.2386$</td>
</tr>
<tr>
<td>$x_2^*$</td>
<td>$\text{Min } f_2$</td>
<td>$f_1(x_2^*) = 12056.5$</td>
<td>$f^{PI}_{2} = 4668.214$</td>
<td>$f_3(x_2^*) = 38.7702$</td>
</tr>
<tr>
<td>$x_3^*$</td>
<td>$\text{Max } f_3$</td>
<td>$f_1(x_3^*) = 18261.3$</td>
<td>$f_2(x_3^*) = 10449.519$</td>
<td>$f^{PI}_{3} = 59.952$</td>
</tr>
</tbody>
</table>

$\text{Min}\{f_{1,2}(x^*)\}$ \quad $\text{Max}\{f_3(x^*)\}$ \quad 18261.3 \quad 10449.519 \quad 30.2386
Table 5. Optimal solution of the case study by the TH method, $\theta_1=0.4$, $\theta_2=0.2$, $\theta_3=0.4$, $\varphi=0.55$

<table>
<thead>
<tr>
<th>Period</th>
<th>Plant</th>
<th>NL</th>
<th>DC</th>
<th>Order of retailers in a route</th>
<th>RC</th>
<th>Nf</th>
<th>CDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>$1\checkmark$ 1 4 6 3 1</td>
<td>1</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>$1\checkmark$ 1 3 7 1</td>
<td>1</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>$1\checkmark$ 1 5 6 4 1</td>
<td>1</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6. Pareto-optimal solutions of the TH method

<table>
<thead>
<tr>
<th>$\varphi$</th>
<th>Objective 1</th>
<th>Objective 2</th>
<th>Objective 3</th>
<th>Satisfaction degree</th>
<th>Computational time</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.55</td>
<td>10518.43</td>
<td>6362.177</td>
<td>67.9</td>
<td>$\mu_T(f)=0.805$</td>
<td>14400</td>
</tr>
<tr>
<td>0.65</td>
<td>10178.19</td>
<td>6193.62</td>
<td>61.03</td>
<td>$\mu_T(f)=0.788$</td>
<td>14550</td>
</tr>
<tr>
<td>0.75</td>
<td>9837.953</td>
<td>6025.061</td>
<td>54.166</td>
<td>$\mu_T(f)=0.769$</td>
<td>14500</td>
</tr>
<tr>
<td>0.85</td>
<td>9830.153</td>
<td>6020.403</td>
<td>53.661</td>
<td>$\mu_T(f)=0.767$</td>
<td>14250</td>
</tr>
<tr>
<td>0.95</td>
<td>9820.352</td>
<td>6015.816</td>
<td>53.156</td>
<td>$\mu_T(f)=0.767$</td>
<td>14300</td>
</tr>
<tr>
<td>Avg.</td>
<td>10037.02</td>
<td>6123.415</td>
<td>57.9726</td>
<td>0.7794</td>
<td>14400</td>
</tr>
</tbody>
</table>

Table 7. Size of test problems

<table>
<thead>
<tr>
<th>No.</th>
<th>Problem size</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$</td>
<td>D</td>
<td>\times</td>
<td>G</td>
<td>\times</td>
</tr>
<tr>
<td>0</td>
<td>$2 \times 2 \times 5 \times 2 \times 2 \times 10 \times 3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>$3 \times 2 \times 6 \times 2 \times 2 \times 20 \times 3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$3 \times 2 \times 8 \times 3 \times 2 \times 25 \times 3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$4 \times 2 \times 12 \times 3 \times 2 \times 30 \times 3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$6 \times 2 \times 18 \times 4 \times 2 \times 40 \times 4$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>$8 \times 3 \times 24 \times 4 \times 3 \times 60 \times 4$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$10 \times 3 \times 30 \times 5 \times 3 \times 80 \times 4$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>$12 \times 3 \times 40 \times 8 \times 3 \times 100 \times 5$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>$15 \times 3 \times 50 \times 10 \times 3 \times 140 \times 5$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>$18 \times 4 \times 60 \times 12 \times 4 \times 180 \times 5$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>$20 \times 4 \times 70 \times 15 \times 4 \times 200 \times 6$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8. Levels of parameters for the NSGA-II

<table>
<thead>
<tr>
<th>NSGA-II Parameters</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>1</td>
</tr>
<tr>
<td>Max iteration</td>
<td>80</td>
</tr>
<tr>
<td>Population size</td>
<td>50</td>
</tr>
<tr>
<td>Crossover probability</td>
<td>0.6</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Table 9. Levels of parameters for the hybrid NSGA-II-MOPSO

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max iteration</td>
<td>80✓</td>
</tr>
<tr>
<td>Population size</td>
<td>50</td>
</tr>
<tr>
<td>Repository size</td>
<td>20✓</td>
</tr>
<tr>
<td>Crossover probability</td>
<td>0.6</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.2</td>
</tr>
<tr>
<td>Beta (Leader selection pressure)</td>
<td>0.8</td>
</tr>
<tr>
<td>Gamma (Deletion selection pressure)</td>
<td>0.8</td>
</tr>
<tr>
<td>Weight of inertia</td>
<td>0.5✓</td>
</tr>
<tr>
<td>Personal learning (c₁)</td>
<td>1</td>
</tr>
<tr>
<td>Global learning (c₂)</td>
<td>1✓</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>RUN</th>
<th>CT(0.2)</th>
<th>NPS(0.2)</th>
<th>DM(0.3)</th>
<th>SM(0.3)</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>105.142</td>
<td>50</td>
<td>21421.1</td>
<td>613.71</td>
<td>0.297885</td>
</tr>
<tr>
<td>2</td>
<td>167.587</td>
<td>100</td>
<td>85098</td>
<td>377.702</td>
<td>0.770914</td>
</tr>
<tr>
<td>3</td>
<td>371.973</td>
<td>(0.5)</td>
<td>47398.1</td>
<td>431.552</td>
<td>0.583718</td>
</tr>
<tr>
<td>4</td>
<td>173.621</td>
<td>(0)</td>
<td>(0)</td>
<td>(0.326282)</td>
<td>0.602067</td>
</tr>
<tr>
<td>5</td>
<td>441.866</td>
<td>(0.5)</td>
<td>44443.6</td>
<td>396.191</td>
<td>0.449012</td>
</tr>
<tr>
<td>6</td>
<td>410.854</td>
<td>(0.47)</td>
<td>(0.361552)</td>
<td>(0.57119)</td>
<td>0.825914</td>
</tr>
<tr>
<td>7</td>
<td>152.874</td>
<td>(0.97)</td>
<td>(0.872801)</td>
<td>(1)</td>
<td>0.526433</td>
</tr>
<tr>
<td>8</td>
<td>449.621</td>
<td>(0)</td>
<td>46711.6</td>
<td>669.836</td>
<td>0.346954</td>
</tr>
<tr>
<td>9</td>
<td>575.734</td>
<td>(1)</td>
<td>(0.602499)</td>
<td>(0)</td>
<td>0.38075</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Problem (0)</th>
<th>2 x 2 x 5 x 2 x 2 x 7 x 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solving method</td>
<td>obj 1</td>
</tr>
<tr>
<td>Exact</td>
<td>10037.02</td>
</tr>
<tr>
<td>NSGA-II</td>
<td>10945</td>
</tr>
<tr>
<td>NSGA-II-MOPSO</td>
<td>10578</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Number</th>
<th>NSGA-II</th>
<th>NSGA-II-MOPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obj 1</td>
<td>Obj 2</td>
</tr>
<tr>
<td>1</td>
<td>23482</td>
<td>9565.29</td>
</tr>
<tr>
<td>2</td>
<td>43904.5</td>
<td>18237.5</td>
</tr>
<tr>
<td>3</td>
<td>53861.5</td>
<td>28073.5</td>
</tr>
<tr>
<td>4</td>
<td>67791</td>
<td>50094.5</td>
</tr>
<tr>
<td>5</td>
<td>96077</td>
<td>75479</td>
</tr>
<tr>
<td>6</td>
<td>163575</td>
<td>90897</td>
</tr>
<tr>
<td>7</td>
<td>262445</td>
<td>153760</td>
</tr>
<tr>
<td>8</td>
<td>371120</td>
<td>212640</td>
</tr>
<tr>
<td>9</td>
<td>584590</td>
<td>312140</td>
</tr>
</tbody>
</table>

Avg. 196028 113070 128.25 246023 111554 140.95

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

<table>
<thead>
<tr>
<th>Number</th>
<th>NSGA-II</th>
<th>NSGA-II+MOPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NPS</td>
<td>CT</td>
</tr>
<tr>
<td>1</td>
<td>149.5</td>
<td>686.01</td>
</tr>
<tr>
<td>2</td>
<td>150</td>
<td>564.84</td>
</tr>
<tr>
<td>3</td>
<td>150</td>
<td>740.79</td>
</tr>
<tr>
<td>4</td>
<td>150</td>
<td>1289.04</td>
</tr>
<tr>
<td>5</td>
<td>150</td>
<td>1829.46</td>
</tr>
<tr>
<td>6</td>
<td>150</td>
<td>2413.91</td>
</tr>
<tr>
<td>7</td>
<td>148</td>
<td>3548.40</td>
</tr>
<tr>
<td>8</td>
<td>150</td>
<td>5357.59</td>
</tr>
<tr>
<td>9</td>
<td>150</td>
<td>7149.93</td>
</tr>
<tr>
<td>10</td>
<td>150</td>
<td>9415.76</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Metrics</th>
<th>NSGA-II</th>
<th>NSGA-II-MOPSO</th>
<th>NSGA-II</th>
<th>NSGA-II-MOPSO</th>
<th>Mean difference</th>
<th>Confidence interval</th>
<th>t-value</th>
<th>DF</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DM</td>
<td>200071</td>
<td>91417</td>
<td>134877</td>
<td>44364</td>
<td>108654</td>
<td>42156 - 175151</td>
<td>3.64</td>
<td>9</td>
<td>0.005</td>
</tr>
<tr>
<td>SM</td>
<td>2305</td>
<td>3639</td>
<td>1486</td>
<td>1728</td>
<td>-1330</td>
<td>-1702 - 968</td>
<td>-8.10</td>
<td>9</td>
<td>0</td>
</tr>
</tbody>
</table>